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Studies in Empirical Policy Evaluation: New Methods and Applications to the Energy Transition

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Studies in Empirical Policy Evaluation: New Methods and Applications to the Energy Transition

By

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Abstract

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The electricity sector is experiencing a period of significant change as policymakers grapple with a range of economic and environmental challenges. Climate change, health, equity, efficiency, reliability and safety are all front of mind. Formulating and enacting policy to tackle these challenges and ensure prosperity in an environmentally stable world means making big decisions with limited understanding of how they will play out. A critical requirement for making progress on these pressing issues is the ability to interrogate the decisions that have been made, quantify their effects, and use that knowledge to make better decisions in the future. The research set out here aims to do exactly that, through developing new empirical methods and applying them in novel ways to two key policy areas in energy and environmental economics.

First I study the phase-out of nuclear power in Germany. Many countries have phased out nuclear electricity production in response to concerns about nuclear waste and the risk of nuclear accidents. In joint work with Olivier Deschenes and Akshaya Jha, we examine the impact of the shutdown of roughly half of the nuclear production capacity in Germany after the Fukushima accident in 2011. We use hourly data on power plant operations and a novel machine learning framework to estimate how plants would have operated differently if the phase-out had not occurred. We find that the lost nuclear electricity production due to the phase-out was replaced primarily by coal-fired production and net electricity imports. The social cost of this shift from nuclear to coal is approximately 3 billion euros per year. The majority of this cost comes from the increased mortality risk associated with exposure to the local air pollution emitted when burning fossil fuels. Even using alternative assumptions regarding the value of avoided health damages and the impact of the phase-out on the deployment of renewable power, the social costs still range from 1 to 8 billion per year. It is challenging to find estimates of the benefits from reduced nuclear operating costs, accident risks and waste disposal that can outweigh social costs of this magnitude.

Second, I study the deployment of renewable energy in the United Kingdom. Large infrastructure projects can create widespread societal benefits and are often critical to tackling major national or global challenges. However, they also frequently prompt strong opposition from local residents and businesses. This is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior, and while it is thought to be common in many settings the economic costs it imposes are poorly understood. In this paper I estimate the economic costs of so-called NIMBYism. To do this I examine the case of renewable energy in the United Kingdom, where I draw on detailed planning data for all renewable energy projects spanning three decades, including projects that were proposed but not approved. I first use hedonic methods to estimate how the construction of a wind or solar project is capitalized into local property values. I find that wind projects have significant negative local impacts whilst solar projects do not. I then quantify the weight that planning officials place on various factors during the planning process and find evidence that they are indeed particularly responsive to local impacts. The result has been a systematic refusal of societally beneficial projects. Ultimately misallocated investment due to the planning process may have increased the cost of the UK's deployment of wind power by 10-25%. A significant portion of this can plausibly be attributed to NIMBYism.

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I also wish to acknowledge my fellow students at the Energy & Resources Group, my fellow graduate student researchers at the Energy Institute at Haas, and the students in the Agricultural & Resource Economics Department that semi adopted me over my time here. You have been a fantastic group to spend the last five years with navigating the bizarre world of graduate study. I look forward to us crossing paths again in the future.

To my co-authors on the work on Germany's nuclear phase-out, Olivier Deschenes and Akshaya Jha, it has been an absolute pleasure working with you both. I hope this is the first of many collaborations to follow.

I woud be remiss if I did not also mention the four undergradutes who provided excellent research assistance collecting planning documents for my project on NIMBYism. Danielle Schiro, Fiona Stewart, Ana Fung and Keanna Laforga, you were a treat to work with and I wish you all the best out there in the real world post-graduation.

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Lastly, I would like to thank my friends and family that have put up with me these past few years. I hope I've made you proud.

Preface

The research set out here develops new empirical methods and then applies them in novel ways to key policy areas relating to energy and environmental economics. This thesis is divided into four chapters, grouped together in two parts based on the two policy applications I study. In both cases I first devote a chapter to making methodological contributions to the toolkit for evaluating energy policies. I then use a second chapter to take the insights created by these new methods to evaluate the policy in question.

Part I focuses on the phase-out of nuclear power in Germany. In Chapter 1 I develop a new machine learning framework for simulating electricity markets. Chapter 2 then takes the findings from applying this new approach and conducts a valuation analysis to understand the costs and benefits created by the phase-out policy. This work is joint with Olivier Deschenes and Akshaya Jha, particularly with respect to the valuation analysis.

Part II focuses on the deployment of renewable energy in the United Kingdom. In Chapter 3 I use hedonic methods to estimate the local impacts of wind and solar projects. As well as building on an existing literature, I also make a number of methodological contributions that enhance the findings from this particular empirical strategy. Chapter 4 then takes these estimates of the local impacts of wind and solar projects and uses them to examine flaws in the process for planning and permitting new renewable energy projects.

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Part I

The Phase-Out of Nuclear Power in Germany

Chapter 1

Simulating the Electricity Market using Machine Learning Methods

1.1 Introduction

There is a growing need to evaluate the many policy changes currently being enacted on energy and environmental issues to understand their realized impacts. Historically studies of the electricity sector have utilized some form of electricity dispatch model that combines engineering and economic modeling tools to simulate the operation of the power grid. These models must explicitly specify firm incentives, such as whether or how firms exercise market power. They must also capture operational constraints such as transmission congestion and plants' start-up and ramping costs. In principle more sophisticated models do include components aimed at tackling these dynamics. However, this inevitably increases model complexity, raising barriers to entry for new users and researchers. Making the assumptions necessary to model these features of electricity markets is also non-trivial.

There is now a wealth of data available on electricity markets in many countries, providing rich opportunities to leverage recent developments in data-driven analysis. Here we set out a new application of machine learning methods to the power sector for the purpose of ex post policy evaulation. Our approach seeks to recover how plants are dispatched based on a host of different variables pertaining to plant operations, demand, and electricity transmission. The primary benefit of this empirical approach is that it requires fewer assumptions regarding firm incentives or operational constraints. We allow the data to tell us how these factors impact plant operations.

There are a wide range of possible applications for the approach we develop here. As an illustration we apply it to study the phase-out of nuclear power in Germany. This was a major piece of energy policy that saw Germany commit to rapidly shutting down its fleet of nuclear reactors, in large part as a response to the Fukushima nuclear crisis in 2011. Our machine learning approach predicts which power plants increased their output in response to the nuclear plant closures. In doing so, this paper contributes a new method that builds on Davis and Hausman (2016) in order to empirically assess how a change in electricity production or consumption at one location propagates throughout the electricity transmission network. This new methodology is useful in a number of different empirical contexts. For example, recent studies have explored how production at different fossil fuel-fired plants responds to changes in electricity consumption at a given location, whether it be plugging in an electric vehicle (Holland et al., 2018), installing a more energy efficient appliance, or siting new wind and solar resources (Callaway, Fowlie and McCormick, 2018*a*). Finally, our paper also contributes to the small but growing literature in energy and environmental economics that integrates machine learning into causal inference techniques (Burlig et al., 2017; Abrell, Kosch and Rausch, 2019).

Our novel machine learning approach combines hourly data on observed power plant operations between 2010-2019 with a wide range of related information, including electricity demand, local weather conditions, electricity prices, fuel prices and various plant characteristics. Using these data, we first replicate prior empirical approaches in order to document that production from nuclear sources declined precipitously after March 2011. This lost nuclear production was replaced by electricity production from coal- and gas-fired sources in Germany as well as electricity imports from surrounding countries. We then more formally estimate the impact of the nuclear phase-out on market outcomes using our machine learning algorithm. This algorithm predicts the quantity of electricity produced by each power plant in Germany in each hour-of-sample under two scenarios: one with the nuclear phase-out and one without it. Consistent with the aforementioned descriptive trends, the results of this estimation procedure indicate that the lost nuclear electricity production due to the phase-out was replaced primarily by coal-fired production and net electricity imports.

In developing this data-driven approach we also discuss its strengths and weaknesses relative to the more structural modelling methods that have tended to dominate studies in this area. For instance, we can only examine scenarios that are sufficiently similar to observed outcomes. This is why other empirical models of wholesale electricity markets tend to focus either on ex-post policy assessments or identifying how marginal changes in electricity demand impact plant operations. Indeed, our chosen application focuses on an ex-post evaluation of the nuclear phase-out in Germany on aggregate market outcomes. Our approach also does not offer robust insights for a given plant in a given hour. As such, our empirical modeling should be seen as a complement rather than a substitute for more explicit simulation modeling of electricity markets.

This is particularly true when the behavior of individuals plants or short-term physical constraints are of interest rather than aggregate market outcomes.

The rest of this paper proceeds as follows. Section 1.2 sets out the data we use, the policy application we examine, and the details of the machine learning approach we develop. Section 1.3 provides the results of our application of this approach to the case study of the phase-out of nuclear power in Germany. Section 1.4 concludes.

1.2 Empirical Strategy

1.2.1 Context of Policy Application and Data

History of Nuclear Power in Germany

The first nuclear power stations were constructed in Germany in the 1960s. Germany's nuclear production capacity expanded rapidly over the next three decades; the last nuclear reactor was commissioned in 1989. Despite no new reactors coming online in the 1990s and 2000s, roughly 25% of Germany's electricity production came from nuclear plants prior to 2011.

Nuclear power has long been controversial in Germany. There were protests as far back as the 1970s at a number of sites where nuclear facilities were either proposed or under construction. However, the Chernobyl disaster in Ukraine in 1986 created a focal point in the politics of nuclear power in Germany. Specifically, radioactive fallout affected much of the country and led to growing public concern. In 1998, the Schröder government took power through a coalition between the Social Democratic Party (SPD) and the Green Party. Over the next two years, the Schröder government banned the construction of new reactors and negotiated a policy of phasing-out nuclear power completely. This plan called for all nuclear reactors to be shut down by 2022.

The center-right Merkel government came to power in 2009. This government renegotiated the original phase-out policy by committing to extending the lifetimes of the newest reactors. This revised policy pushed back the shutdown of the last nuclear reactor into the 2030s. However, the specter of nuclear disaster rose again due to the Fukushima incident on March 11, 2011. In response, public opposition to nuclear intensified again, with an estimated 250,000 people taking to the streets nationwide to protest in the days and weeks following March 11, 2011. The resulting political pressure forced the Merkel government to declare a moratorium on planned extensions at existing nuclear power plants almost immediately after the Fukushima incident. In addition, eight older reactors were taken offline for testing.

By May of 2011, German policymakers decided to return to a version of the original plan: phase out all nuclear power by 2022. Specifically, of the seventeen reactors operating in 2011, the eight reactors already temporarily offline were closed immediately (8.4 GW of capacity), a ninth reactor was closed in 2015 (1.3 GW), a tenth in 2017 (1.3 GW), an eleventh in 2019 (1.4 GW), and the final six reactors (8.1 GW) will close in 2022. Our sample period ends in 2019. Consequently, our empirical analysis focuses on the closure of the nuclear reactors in 2011, 2015, 2017 and 2019, but not the subsequent closures in 2022.

The phase-out of nuclear power is part of a wide-ranging transformation of Germany's energy sector known as the *Energiewende*. The primary goal of this policy is to reduce Germany's carbon emissions by at least 80% by 2050 relative to 1990 levels (BMWi, 2018). To achieve this, Germany has undertaken major investments in renewable electricity production, transmission grid infrastructure, and energy efficiency measures. The sweeping scope of the *Energiewende* policy highlights the importance of accounting for a host of potential time-varying confounders when assessing the impact of the nuclear phase-out. This motivates the development of the machine learning approach set out here.

The Germany Electricity Sector

This paper brings together a wide range of publicly available data on the German power sector from a variety of different sources. First, we obtain data on the hourly operation of the electricity grid in Germany from the European Network of Transmission System Operators for Electricity (ENTSOE). This includes hourly data on total electricity demand, aggregate electricity production by source type, imports and exports in and out of Germany at border points, and hourly day-ahead electricity prices. ENTSOE also provide data on unit-level electricity production for all power plants with production capacity greater than 100MW.

Importantly the ENTSOE data are only available from 2015-2019. We therefore supplement these with additional data on hourly total production by source (e.g. nuclear, coal, natural gas, oil, etc.) from the European Energy Exchange (EEX) from 2010-2019. Additional data on wholesale electricity prices comes from Thomson Datastream. We also integrate data from Germany's four different transmission system operators (TSOs) that are each responsible for a different geographical area on the German grid: Amprion, TenneT, TransnetBW and 50Hertz. Each TSO reports hourly production from wind and solar sources for the period 2010-2019. The TSOs also provide data on the hourly level of electricity imports and exports in and out of Germany at border points, as well as the hourly total quantity of electricity demanded for their portion of the grid. Combining the data from ENTSOE with the additional data from EEX, Thomson and the TSOs allows us to construct consistent hourly series from the entire 2010-2019 period.

We construct each plant's marginal cost over time using data on input fuel prices and carbon emission prices gathered from the following two main sources. First, Thomson Datastream provides data on daily natural gas prices in Germany and neighboring countries. The Intercontinental Exchange (ICE) lists monthly coal and oil prices as well as the monthly permit prices for carbon dioxide emissions set by the European Union Emissions Trading System (EUETS). Assumptions on marginal costs for other sources such as nuclear, wind and solar are taken from a range of industry sources.

Finally, we compile other electricity sector data and power plant level characteristics from a variety of different sources (Open Power System Data, 2018; BNetzA, 2018; Egerer, 2016).

Taken together, our main estimation sample covers the period 2010-2019 and contains hourly data on wholesale electricity prices, hourly total and net electricity demand, hourly production by dispatchable sources, individual power plant characteristics (including hourly marginal costs of production), and hourly plant-level generation (for the 2015-2019 only).

Figure 1.1 presents annual total electricity production in Germany by source as well as total imports and exports. This figure documents the precipitous drop in nuclear production following the 2011 closure of nine reactors as well as the rapid growth in production from wind and solar resources over our 2010-2019 sample period.

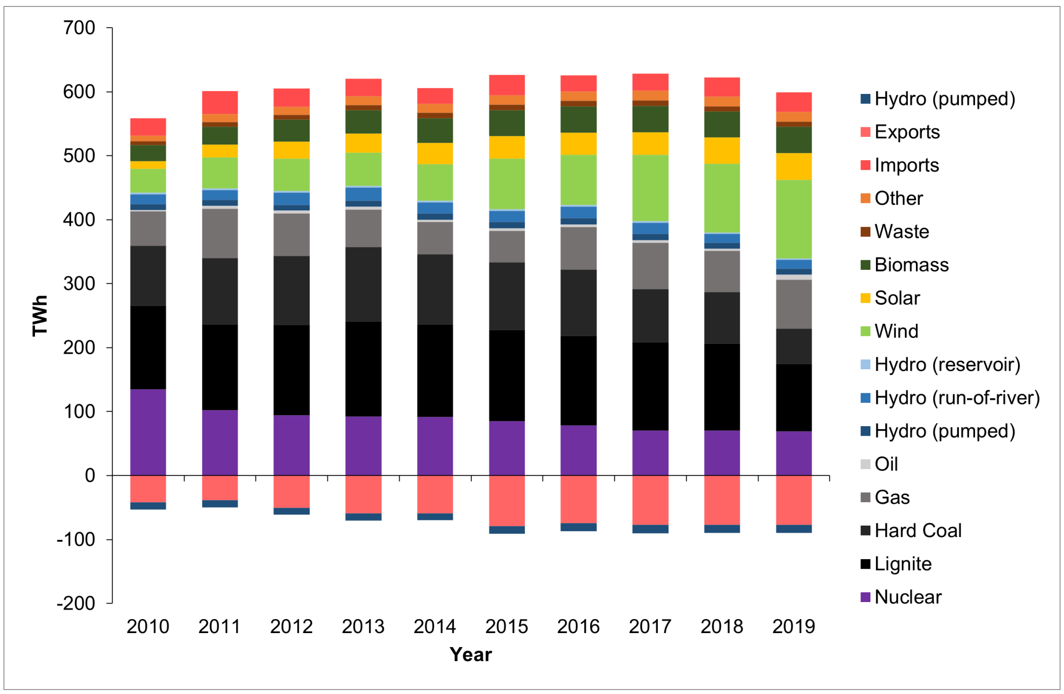
Figure 1.2 shows the estimated marginal cost of each power plant in our sample operating in 2011. We assume that biomass, waste, hydroelectric, wind and solar resources have zero marginal operating cost. Marginal costs for fossil fuel plants are calculated as the sum of fuel costs and an assumed amount of variable operating and maintenance costs that differs by fuel type.[1] Lastly, we assume that nuclear plants have a marginal operating cost of approximately €10/MWh based on prior research on Germany's power sector (Egerer, 2016). This is confirmed by company reports from two European nuclear plant operators: RWE and EDF which also have marginal fuel costs of approximately €10/MWh.[2]

Figure 1.2 highlights that nuclear units uniformly have lower marginal costs than fossil-fuel-fired units. Nuclear power plants also emit virtually no carbon dioxide or local pollutants. We would thus expect that the shutdown of nuclear reactors will lead to increases in both production costs and pollution emissions. We test this hypothesis using a simple event study framework in the next

[1]Fuel costs are converted to euros per MWh using the plant's thermal efficiency: how well the plant converts units of input heat to units of electricity output.

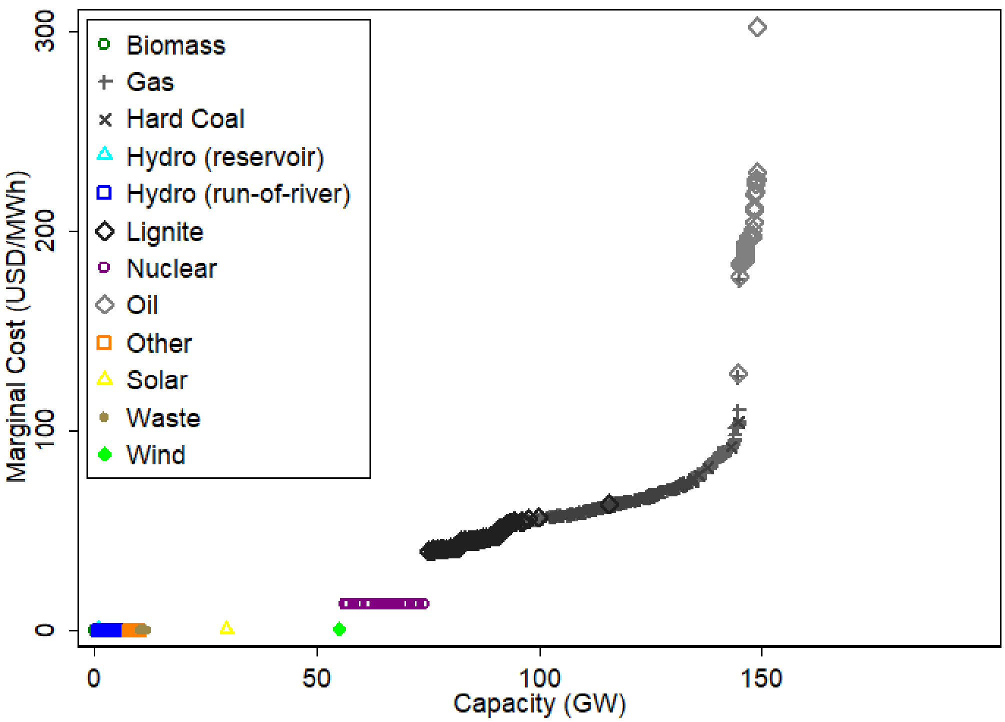
[2]Later in the analysis we do account for non-fuel costs as these can be substantial. The same industry reports indicate these likely amounting to a further €20/MWh resulting in overall costs for the continued operation of existing nuclear plants of roughly €30/MWh.

Figure 1.1: Electricity Production by Source: 2010-2019



Notes: This figure plots the annual total quantity of electricity produced by different types of sources in Germany from 2010-2019. We also plot the annual total quantity of electricity imports and exports for this same sample period. The data underlying this figure are from BNetzA Monitoring Reports.

Figure 1.2: Marginal Cost Curve in 2011



Notes: This figure plots the estimated marginal costs for power plants in Germany in 2011. Specifically, plants are ordered in terms of marginal cost to create an aggregate supply curve. For a given marginal cost c (plotted on the y-axis), the x-axis provides the sum of the production capacity (in GW) over all plants with marginal cost less than or equal to c. For coal, gas and oil plants, marginal costs are calculated as the sum of fuel costs and an assumed variable operating and maintenance cost that differs by fuel type. Fuel costs are converted to dollars per MWh using the plant's thermal efficiency (a measure of how well a plant converts units of input heat to units of electricity output). For this figure, we consider the fuel costs on February 1st, 2011. Nuclear plants are assigned a marginal cost of €10 per MWh as in (Egerer, 2016). Hydro, wind and solar are assumed to have zero marginal costs. For simplicity, the small amount of remaining sources are also assigned a marginal cost of zero (i.e. biomass, waste and other). For ease of presentation, this figure does not show how electricity imports and exports factor into the aggregate supply curve; importantly, we account for imports and exports in our analysis.

section and then build on this to look more comprehensively using our machine learning approach.

1.2.2 Event Study Approach

In response to the Fukishima nuclear accident, the German government suddenly and unexpectedly shut down eight nuclear reactors on March 15^{th} 2011. We can thus analyze the impact of these closures on market outcomes using the event study framework formulated in Davis and Hausman (2016) and more recently implemented by Grossi, Heim and Waterson (2017). Specifically, our event study framework estimates how total electricity production by each fuel type i in each hour-of-sample t responds to changes in electricity demand before versus after March 15th, 2011.

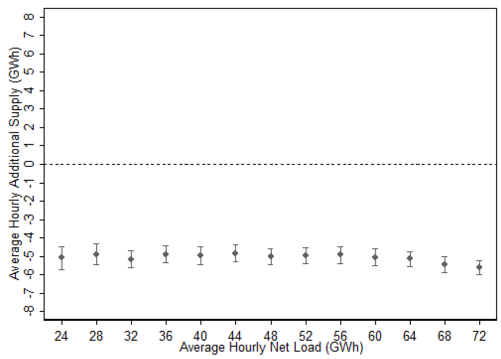
The independent variables of interest are equally-spaced bins of net electricity demand interacted with an indicator for observations after March 15^{th} 2011. As in the rest of this paper, "Net electricity demand" is defined to be electricity demand net of production from renewable sources. We consider net demand because production from renewable sources has near-zero marginal costs and is "non-dispatchable": wind and solar sources produce only when the wind is blowing or the sun is out. In order to implement the event study, we restrict the sample to observations less than 12 months before or after March 15^{th} 2011 and estimate the following regression:

$$G_{i,t} = \sum_b [\mathbf{1}\{L_t \in B_b\}(\alpha_{i,b} + \beta_{i,b} \cdot \mathbf{1}\{t \geq 3/15/2011\})] + \gamma_m + \epsilon_{i,t} \tag{1.1}$$

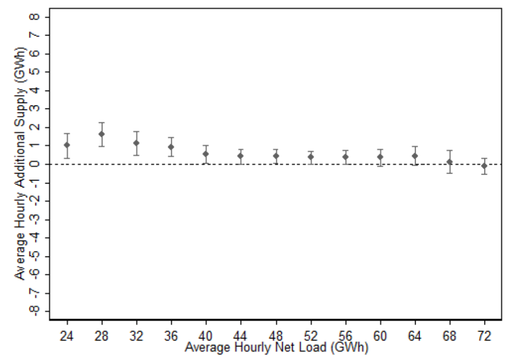
where $G_{i,t}$ is the total quantity of electricity produced by fuel type i in hour-of-sample t in Germany. L_t is net demand in hour t, and $\mathbf{1}\{L_t \in B_b\}$ is an indicator that takes on the value one if L_t is in bin B_b and is zero otherwise. Next, the indicator $\mathbf{1}\{t \geq 3/15/2011\}$ takes on the value one if the observation corresponds to an hour-of-sample on or after March 15^{th} 2011 and is zero otherwise. Finally, we include month-of-year fixed effects (i.e.: γ_m) and cluster standard errors by week-of-sample.

Figure 1.3 plots the coefficient estimates of interest (i.e.: $\hat{\beta}_{i,b}$) along with their 95% confidence intervals. Panel a of this figure shows that average hourly electricity production from nuclear sources dropped by roughly 5 GWh across all levels of net demand. Panels b-d demonstrate that this lost nuclear production was offset in large part by increases in electricity production from fossil fuel fired sources. Specifically, production from lignite increased by roughly 1 GWh on average at low levels of net demand. Production from hard coal increased by 2-3 GWh on average across all levels of net demand. Finally, gas-fired electricity generation also increased by roughly 2 GWh on average, and by as much as 6 GWh for hours-of-sample with very high net demand.

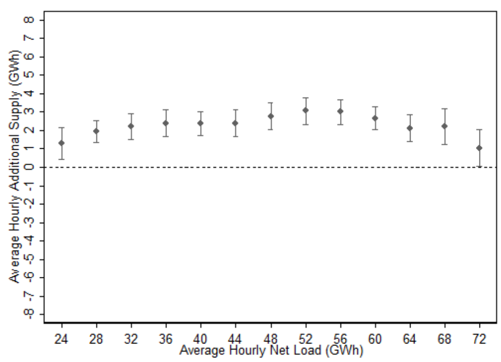
Figure 1.3: Event-Study Estimates of the Effect of the 2011 Nuclear Closures on Fossil Electricity Production



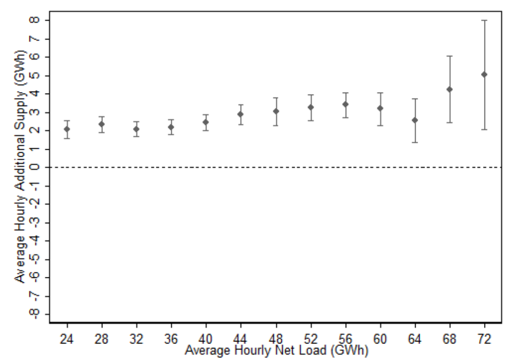
(a) Nuclear



(b) Lignite



(c) Hard Coal



(d) Natural Gas

Notes: This figure plots the results from an event study analysis of the effects of the nuclear phase-out in Germany in 2011. The estimates correspond to changes in electricity production by source after the phase-out, relative to before March 15, 2011. Panel a presents the estimates for nuclear production, separately for each bin of net demand (i.e., electricity demand minus production from renewables). Panels b-d present the corresponding estimates for production from lignite, hard coal, and natural gas, respectively. The panels also include the point-wise 95% confidence interval around each of the estimated effects; the standard errors used to construct these confidence intervals are clustered by week-of-sample.

While these results provide a simple examination of the data, the event study approach has several limitations in our context. First, hourly plant-level data on electricity production are not available prior to 2015. Consequently, the event study framework cannot be used to explore heterogeneity in how different plants respond to the nuclear phase-out beginning in 2011. This heterogeneity is especially important because the amount of local air pollution emitted per MWh of production can vary significantly across plants burning the same type of fuel. In addition, the monetary damage from local air pollution emissions is also tied directly to the number of people exposed to this pollution; the same level of pollution emissions from two different plants can have very different damages based on the number of people living near each of these plants.

Second, the event study framework relies on the assumption that changes in power plant operations around March 15, 2011 are caused by the nuclear reactor closures rather than changes in other factors that determine production behavior. To ensure that this assumption holds, we examine the impact of the phase-out in a fairly narrow window around the initial 2011 shutdowns. Focusing on this narrow window allows us to argue that firms could only respond to the nuclear shutdowns in the very short-run by adjusting output. However, subsequent nuclear plant shutdowns occurred incrementally and were pre-announced. As such, firms may have been able to take actions in anticipation of these later closures.

Finally, other important economic factors also changed over our 2010-2019 sample period independent from the nuclear phase-out in 2011. For example, coal and natural gas plants had similar marginal costs in 2011. However, coal prices decreased precipitously from 2011-2015 while natural gas prices increased over this period. Coal plants were thus increasingly more likely to produce in place of natural gas plants from 2011-2015 even absent any changes in nuclear power production. In addition, many older coal and gas plants were retired between 2010 and 2019, and a number of new fossil fuel-fired plants came online during this period as well. Summarizing, it is unlikely that market outcomes before versus after March 2011 were driven solely by the phase-out, especially as we look further in time after the 2011 shutdown decision.

1.2.3 Machine Learning Approach

We develop a machine learning approach to more credibly estimate the full market and environmental impacts of policy changes in the electricity sector. In this case we study the series of nuclear plant closures that occurred over the entire period between 2011 and 2019. This machine learning approach has two advantages over the event study framework discussed in the previous section. First, hourly plant-level data on electricity production are not available prior to 2015; for this reason, we estimate the event study regressions using data on hourly aggregate electricity production by fuel type. As we noted earlier, plant-level heterogeneity is particularly important for estimating the damages from local air pollution exposure: different plants burning the same type of fuel may have very different emissions factors and number of people living nearby. The machine learning algorithm allows us to use hourly plant-level data from 2015-2019 to estimate plant-level heterogeneity in response to the nuclear phase-out over our entire 2010-2019 sample period.

Second, as discussed earlier, a variety of economic factors relevant for electricity production decisions changed over time independently from the nuclear phase-out. The event study framework affords us only limited ability to control for these factors. In contrast, the machine learning approach allows us to estimate the impact of the nuclear phase-out on plant-level economic and environmental outcomes controlling for a wide range of observed market factors.

Importantly, the goal of our machine learning framework is to best predict market outcomes for different values of the input variables. This differs from traditional econometric methods in two ways. First, we do not seek to identify the causal effect of one variable on another. Second, though we are able to provide bounds on our estimates, it has proven impossible to derive standard errors on the predictions from machine learning models absent randomization of treatment and control groups (Wager and Athey, 2018). Summarizing, our machine learning algorithm gives us substantially more accurate predictions of market outcomes than the event study approach at the cost of being unable to conduct traditional statistical inference on these predictions.

Constructing the Training Dataset

We train our machine learning algorithm to predict power plant operations using a data set of roughly 4.5 million observations. The outcome of interest is the hourly quantity of electricity produced by each "dispatchable" plant in our sample. We subtract "non-dispatchable" renewable output from electricity demand because renewables have near-zero marginal cost and thus produce whenever nature permits (e.g., the sun is out or the wind is blowing). Hourly data on plant-level electricity production are available for all EU member states since 2015 from ENTSOE.[3] We incorporate electricity imports and exports at each border interconnection between Germany and its neighboring countries into our framework by treating each border interconnection point as if it is a power plant. For example, consider the hourly net electricity imports from France to Germany. If France exports 50MWh of electricity to Germany, this border point would be "producing" 50MWh. Conversely, if France imports 50MWh of electricity from Germany, this border point would be "producing" -50MWh.

The dependent variables considered in our machine learning framework are the production levels from each power plant and border points in our sample. In all cases, we normalize the relevant dependent variable by dividing output

[3]More specifically, the data are available for plants with capacity greater than 100 MW. This covers 100% of production from nuclear plants, 95% from lignite plants, 85% from hard coal plants, 50% from gas plants and 45% from oil plants. We treat the operating behavior of these plants as being representative of the remaining plants with capacity less than 100MW, conditional on a range of other plant characteristics such as technology type, combined heat and power functionality, location, and so on.

by the maximum production capacity of each power plant or the maximum transfer capacity of the border point as applicable. Our algorithm focuses on dependent variables that are bounded between 0 and 1; we rescale the flows from border points from their original scale of -1/1 to 0/1 when applying the algorithm. We refer to this rescaled output as the operating rate for each power plant.

The independent variables include net electricity demand, local weather, each plant's marginal cost, the availability of other power plants, and a wide range of power plant characteristics such as fuel type, efficiency, technology, and location. We estimate a predictive model that takes these independent variables as inputs and outputs a predicted operating rate for each power plant in each hour. Importantly, we have data on these independent variables from 2010-2019. This allows us to predict hourly, plant-level electricity production from 2010-2019 using our model despite only observing hourly plant-level production from 2015 onward.

We also build a predictive model for wholesale electricity prices. However, there is no cross-sectional variation in these prices; the hourly wholesale electricity price is the same throughout Germany. In this case, the independent variables for the time-series model of electricity prices include electricity demand, national average weather, and the marginal cost associated with the marginal unit (i.e.: the unit with the largest marginal cost that produces a positive quantity in that hour-of-sample).

Random Forest Algorithm

We predict outcomes using a Random Forest regression algorithm (Breiman, 2001). In particular, we use the Quantile Regression Forest algorithm (Meinshausen, 2006). Random forests are especially well-suited for our empirical context for several reasons.

First, each plant's production is based on a potentially complex combination of factors such as the marginal costs and availability of other plants, electricity demand at different locations, and transmission constraints. Consequently, the relationship between plant-level production and the independent variables listed above is likely to be highly non-linear and include multiple interactions. Random forest methods are well-suited to use variation in the data in order to find these interactions rather than pre-specifying how independent and dependent variables relate using polynomials or splines as in a more standard regression framework.[4]

[4]In their application for predicting housing values, Mullainathan and Spiess (2017) report that the Random Forest method results in the most accurate predictions, as measured by out-of-sample R^2, among the various methods evaluated (e.g., OLS, Regression Tree, LASSO, and Ensemble).

Second, the Random Forest algorithm ensures that the support of possible outcome predictions is bounded by the support of the outcome values in the training data set. This prevents nonsensical predictions such as plants producing negative amounts of electricity or producing greater than their capacity (e.g. operating rates above 100% or below 0%).

Third, the Quantile Regression Forests algorithm produces predictions for the full conditional distribution of the outcomes rather than just their expected value. This property both allows us to better understand the uncertainty in our analysis and to make corrections that ensure that our predicted outcomes meet certain physical constraints (e.g., that electricity supply equals electricity demand). This is important because there is clearly uncertainty about whether a given plant will operate in a given hour conditional on the covariates for that plant-hour. However, being able to characterize the distribution of potential outcomes means we can (a) examine the uncertainty in our results, and (b) adjust our final estimation to calculate the most likely changes to in plant-level production that still meet physical requirements (i.e. that demand equals supply). For example, though our primary specifications report the conditional averages of predicted outcomes, we find that both the mean and median of the potential predictions produced by our model perform reasonably well (see Figure 1.6).

Feature Scaling and Importance

The most important independent variables for our analysis are:

- *Net Load.* Net load is defined as total electricity demand minus production from low marginal cost or non-dispatchable sources. Specifically, we subtract production from renewables (wind, solar, hydro, biomass, waste) and nuclear. This net load variable thus measures the amount of production required by "flexible" (typically fossil-fuel fired) sources.[5]

- *Marginal Cost.* A plant decides whether to produce primarily based on whether its marginal cost is less than the electricity price it will be paid for its output. In electricity markets such as Germany's, the electricity price is typically set by the highest marginal cost plant necessary to meet demand (i.e. the clearing plant that is on the margin). Consequently, we first construct estimates of each plant's marginal cost over time. We then estimate the marginal cost of the clearing plant: the last fossil plant (or border point) necessary to meet net load in a given hour. Finally, we construct a "standardized" marginal cost for each plant as the plant's marginal cost minus the marginal cost of the clearing plant for that hour.

[5]We also include lags and leads of net load to capture the fact that many power plants have dynamic production constraints (e.g. the speed at which they can "ramp up" their output, or the minimum amount of time they have to be offline before they can restart).

Plants typically produce (don't produce) if this standardized marginal cost is negative (positive).

- *Available Capacity.* Where the "marginal cost" variable captures the position of a plant in the supply curve in terms of price, the "available capacity" variable captures the position of a plant in the supply curve in terms of quantity. For each plant, we calculate the total amount of capacity from other fossil plants (or border points) with a lower marginal cost. Our "available capacity" variable is then calculated as the total amount of capacity with a lower marginal cost than the plant minus net load for that hour. Once again, plants with negative available capacity are likely to produce, while plants with positive available capacity are unlikely to produce.

Figure 1.4a illustrates the relative importance of each of our covariates. As expected, net demand, marginal cost and available capacity are all particularly important covariates. However, it is noteworthy that two of the other important covariates are the type of source (i.e. lignite, hard coal, gas, oil or border point) and whether a fossil-fuel-fired plant is combined-heat-and-power. This reflects the fact that different types of electricity generators face different operational constraints. For example, many natural gas plants in Germany are combined-heat-and-power. As such, whilst they may have higher marginal costs than coal plants, they receive revenues both for their electricity output and from providing heating services. Consequently, combined-heat-and-power plants operate more frequently than would be suggested by simply comparing their marginal cost to electricity prices.

When making out-of-sample predictions using a predictive model such as this, it is important to ensure that the training data-set provides sufficient support across the predictor variables. This is because our algorithm is ill-suited to extrapolate beyond the economic conditions seen in the training data. We are confident that assessing the impacts of nuclear phase-out is an interpolation exercise rather than extrapolation exercise in part because the portfolio of fossil-fuel power plants and the underlying transmission grid does not change very much over our 2010-2019 sample period.

Rescaling certain variables can also help to ensure that our out-of-sample prediction is not extrapolating too far outside the support of the training data.[6] The three main variables we use to approximate the interaction between supply and demand are net load, plant marginal costs, and the amount of available capacity. Almost by definition, the counterfactual no-phase-out scenario will contain some periods where these variables fall outside the range in the training

[6]For example, we rescale the marginal costs of each plant by the marginal cost of the last plant needed to clear the market. Even if fuel costs doubled from 2010-2019, for example, the rescaling would ensure that the rescaled marginal costs fed into our algorithm stay within a reasonable range over our sample period.

dataset. Even so, there is such wide variation in electricity demand, production from renewables and marginal costs that the overlap in support between these variables in the factual versus counterfactual scenarios is very good. This can be seen in Figures 1.4b, 1.4c and 1.4d.

Implementation for our Policy Application

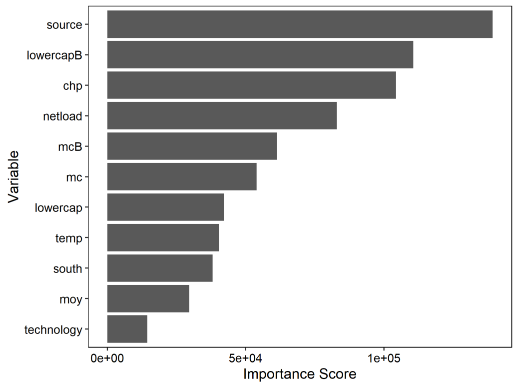
We use the trained machine learning model to construct two data series. First, we predict hourly plant-level electricity production at each dispatchable plant (i.e., each fossil plant or border point) using the observed values of the independent variables over 2010-2019. This provides us with electricity production levels at each plant in the "factual" scenario with the nuclear phase-out. We note that the machine learning model is necessary for estimating plant-level production even in the factual scenario because there is no hourly plant-level production data prior to 2015.

Second, we use the model to estimate hourly production for the same set of dispatchable plants in the counterfactual scenario where there was no nuclear phase-out. Put another way, we predict plant-level production assuming that the nuclear reactors that were shut down in 2011, 2015, 2017 and 2019 would have remained operational until the end of 2019. To do this, we first calculate the amount of electricity these nuclear plants would have produced in each hour-of-sample if they had remained online.[7] We subtract this counterfactual nuclear output from net electricity demand, thus reducing the production needed from the remaining dispatchable plants.

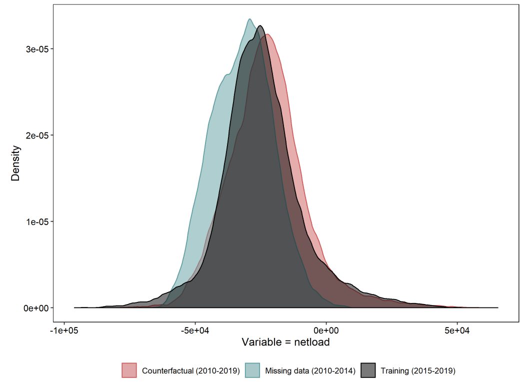
The machine learning application we use is designed to predict how dispatchable flexible sources such as fossil-fuel plants and border flows increase or decrease their output in order to meet the residual demand left after accounting for output from renewables and nuclear sources. Net load, the relative marginal cost of each plant, and the amount of alternative available capacity are key predictors in the analysis not only because they play a significant role in explaining plant operating decisions, but also because they are the variables we modify in order to construct the counterfactual scenario. For the scenario with the phase-out, the net load variable is the observed net load given the phase-out decision as shown in Figure 1.5a. For the counterfactual scenario without the phase-out, nuclear production would have been higher and so net load would have been lower, as shown in Figure 1.5b. This reduction in net

[7] We assume that the nuclear plants that were shut down would have operated at 80% of their capacity on average. We choose this relatively conservative 80% operating rate because the nuclear plants that were shut down tended to be older; newer nuclear plants often achieve operating rates of 90-95%. We adjust this counterfactual nuclear output based on observed fluctuations in monthly total nuclear production from 2012 to 2014 because there were no nuclear shutdowns during this period. This adjustment primarily reflects the fact that nuclear plants tend to go on maintenance during the summer months when demand is lowest.

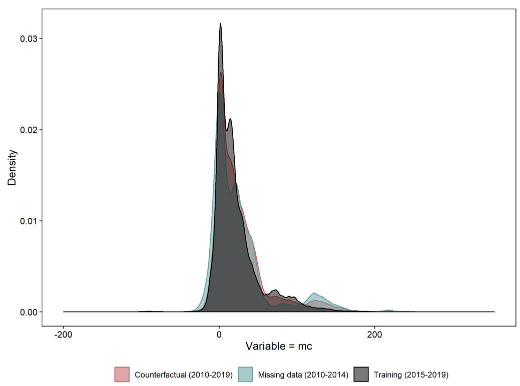
Figure 1.4: Machine Learning Model Diagnostics



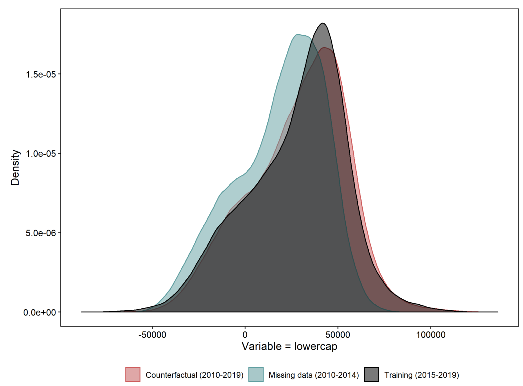
(a) Variable importance scores



(b) Support of Net Demand



(c) Support of Marginal Cost



(d) Support of Available Capacity

Notes: This figure illustrates a range of key model diagnostics related to the machine learning estimation. Panel (a) shows the importance scores for each of the variables included in the estimation. Importance scores indicate the relative importance of each variable in predicting the outcome of interest. The abbreviated names in the figure are as follows: source = source type (e.g. lignite, hard coal, gas, oil or border); mc = marginal cost relative to the clearing unit; mcB = marginal cost relative to the clearing unit including border capacity; lowercap = amount of capacity with a lower marginal cost; lowercapB = amount of capacity with a lower marginal cost including border capacity; chp = presence and scale of combined-heat-and-power capability; technology = technology type (e.g. steam turbine, combined cycle turbine or transfer); temp = local temperature; south = indicator for whether the plant or border point is located in the south of the country; moy = month-of-year; dow = day-of-week; hod = hour-of-day; netload = electricity load minus production from wind, solar, hydro and nuclear sources; netloadX = difference between current net load and net load X hours ago; netload_X = difference between current net load and net load X hours ahead. Panels (b-d) show the support of three key variables: net demand, standardized marginal cost and available capacity. The grey area shows the distribution of observations in the 2015-2019 training data-set (i.e.: where we have hourly, plant-level production data). The blue area shows the distribution of observations in the missing 2010-2015 data (i.e.: where we only have hourly data on production by fuel type). The red area shows the distribution of observations in the counterfactual scenario (i.e.: without the nuclear phase-out) across the full 2010-2019 analysis period.

load also changes the marginal cost and available capacity variables. Specifically, if net load is lower, the marginal cost of the clearing plant would also be lower. Moreover, the amount of capacity below net load is also lower for lower values of net load. This is illustrated in Figures 1.5c and 1.5d.

Using the median predictions we find around 40 TWh per year of additional supply from higher fossil-fuel plants and net imports. However, it is important to note that there is no constraint in our estimation process that the total amount of estimated replacement production should match the lost nuclear output. In fact, the amount of lost nuclear production is around 50 TWh per year and so using the median predictions actually leads us to under-estimate the level of replacement generation. To remedy this, we utilize the information our quantile regression model provides us on the full conditional distribution of potential changes to output. Specifically, we generate predictions for the 10th, 25th, 40th, 50th, 60th, 75th and 90th percentiles of each of our outcomes. We then find the combination of these percentiles that fully replaces the lost nuclear generation with the most likely set of plant-level changes (i.e. closest to the median). Put another way, we find the percentiles closest to the median that produce a change in annual total generation equal to the annual lost nuclear output. Ensuring that additional supply exactly meets lost nuclear output only requires moving a few percentiles from the median.

Finally, our exposition here has focused on hourly plant-level production. However we do also utilize a similar approach to assess the impact of the phase-out on wholesale electricity prices.

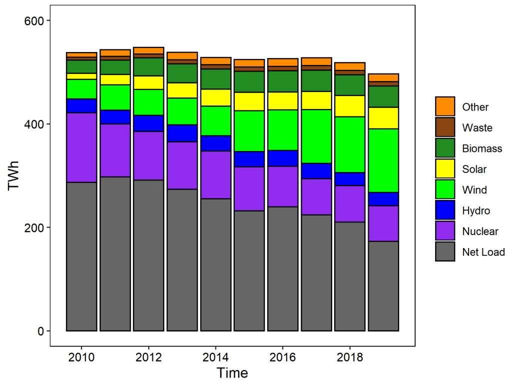
Accounting for Other Impacts of the Policy

A natural concern with the approach as set out thus far is that the phase-out led to changes in other independent variables beyond the direct reduction in nuclear electricity production. For the vast majority of the other independent variables that do not depend on net demand we hold them fixed at their observed values. Given these generally relate to factors like plant characteristics, temperature, and seasonality of demand this assumption seems reasonable. The main exception to this that we account for is the impact of the phase-out on investment in renewable production sources such as wind and solar.

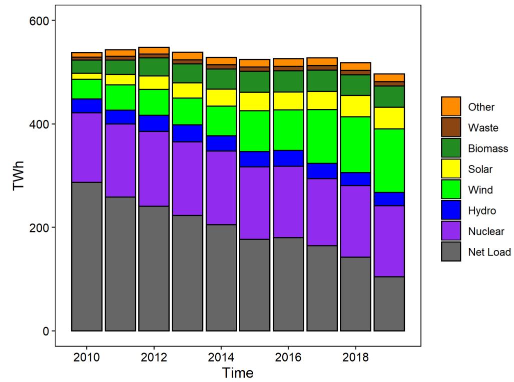
In the absence of the phase-out the incentives to invest in renewables might not have been as strong. To account for this, we assume that renewable production in the no-phase-out scenario would have been 30 TWh lower by 2020. We chose 30 TWh based on changes made to Germany's renewable energy targets in response to the phase-out decision.[8] Reducing renewable production

[8]Specifically, in 2010, Germany planned on producing at least 30% of its electricity from renewables by 2020. However, this target was increased to 35% following the 2011 phase-out decision (Jacobs, 2012). The difference between these two targets requires a change in

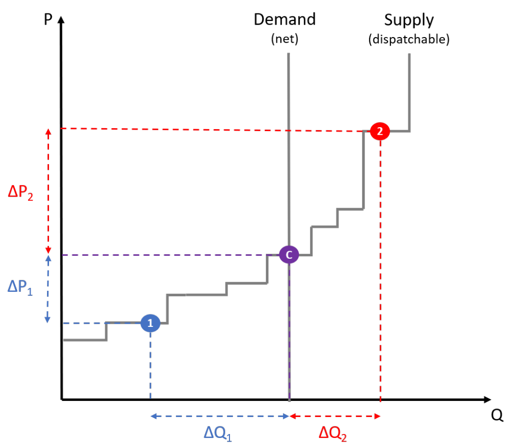
Figure 1.5: Net Demand and Scenario Implementation



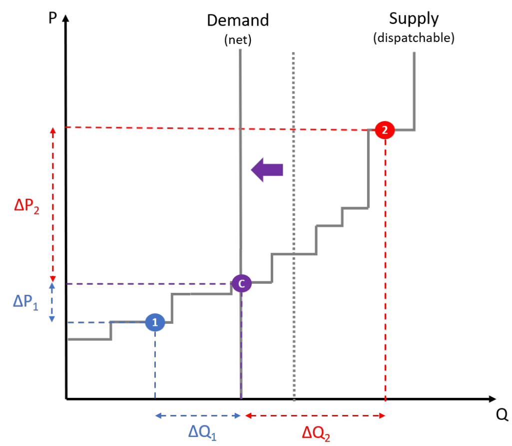
(a) Estimated Net Demand (With Phase-Out)



(b) Estimated Net Demand (Without Phase-Out)



(c) Net Demand Illustration (With Phase-Out)



(d) Net Demand Illustration (Without Phase-Out)

Notes: This figure illustrates the role of the net electricity demand variable in the analysis. Net demand is defined as total electricity demand minus production from low marginal cost or non-dispatchable sources. Specifically, we subtract production from renewables (wind, solar, hydro, biomass, waste) and nuclear. Panels (a) and (b) show the level of net demand both with and without the phase-out respectively. Note that production from renewables is growing over time, which results in less net demand to be satisfied by flexible sources such as fossil-fuel fired plants. Comparing panel (a) to panel (b) shows that more nuclear production without the nuclear phase-out leads to less net demand to be satisfied in this scenario. Panels (c) and (d) provide an illustration of how changing net demand impacts the estimation process. This happens because altering net demand alters the position where net demand intersects with the supply curve of dispatchable capacity. This intersection point is indicated by the clearing fossil-fuel plant (or border point) that is "on-the-margin" (purple). Altering the clearing fossil plant (or border point) affects the relative marginal cost (ΔP) and available capacity (ΔQ) values for all dispatchable supply. These two variables are illustrated for a high marginal cost plant (red) and a low marginal cost plant (blue).

by 30 TWh amounts to an 8% increase in net electricity demand by the end of our study period for the counterfactual case where the phase-out had not gone ahead. We argue that this 8% change in net electricity demand is a relatively large response to attribute to renewables being incentivized by the phase-out.[9] To demonstrate the sensitivity of our findings to these kinds of shifts in net electricity demand we also explore a lower bound scenario where there is no response from renewable investment and an upper bound scenario where the response from renewables is twice as large.[10] These findings are presented and discussed in the robustness analysis.

It is also plausible that the phase-out altered the incentives to invest in fossil power plants as well. Prior studies have demonstrated that, if the phase-out had not occurred, the amount of fossil fuel-fired capacity necessary to ensure that demand is met during peak hours in Germany would have been 4 GW lower by 2020 (Traber and Kemfert, 2012) and 8 GW lower by 2030 (Knopf et al., 2014). However, this reduction in capacity could be due either to fewer new fossil plants being built or to older existing plants closing early. As such the impact on the composition of fossil fuel plants in terms of operating costs and emission intensities is unclear and accounting for this response to the phase-out is unlikely to significantly alter our findings.

In addition to altering the incentives to invest in electricity production capacity, reductions in wholesale electricity prices in the absence of the phase-out may have increased total consumer demand for electricity. In general this kind of effect would lead to an increase in net electricity demand. Thus it has the same directional impact as the various renewable investment scenarios we explore. We therefore argue that our existing renewables sensitivity analysis should help capture the scope for total customer demand to also respond to the phase-out. Specifically, our central assumption of shifts in renewables investment leading to an 8% change in net demand due to the phase-out is already a large response. We consider that there are good reasons to think that changes in wholesale prices would only have a muted impact on customer demand by comparison.[11]

renewable production of roughly 30 TWh between 2010 and 2020.

[9]For example, previous research on the phase-out assumed that investments in renewables did not accelerate due to the nuclear plant closures (Traber and Kemfert, 2012; Knopf et al., 2014). Furthermore, the increases in wholesale electricity prices resulting from the phase-out were unlikely to impact the profitability of investment in renewable capacity. This is because all renewable capacity in Germany is remunerated through feed-in-tariffs that provide a guaranteed above-market price for the electricity produced.

[10]In this case we assume there are 60 TWh of additional renewables by 2020 directly as a result of the phase-out.

[11]This is because the commercial and residential customers that make up around half of Germany's total demand are highly price-inelastic. Moreover, wholesale electricity prices are only roughly a quarter of their overall retail price, with the remainder being network charges, taxes, and renewable subsidy fees(BNetzA, 2018). The latter of these is also inversely related to changes in wholesale prices. It is true that larger industrial customers may be more

1.3 Results

1.3.1 Model Performance

Figure 1.6a compares observed hourly plant-level operating rates (i.e., percentage of capacity utilized) with the predictions from the machine learning model. Specifically the predicted electricity production (scaled on the y-axis) is plotted against the observed production (x-axis) so that observations on the 45 degree line indicate perfect prediction accuracy. Each pixel in the figure represents the predicted vs. actual operating rate in increments of 2% and darker areas correspond to a higher number of plant-hour (or plant-year) observations.

We check the out-of-sample cross-validated performance to avoid overfitting and give a fair assessment of how the model may perform when used to make predictions about our counterfactual no-phase-out scenario. The cross-validated out-of-sample R^2 is 0.53 and the mean squared error (MSE) is 0.059.

However, even this small level of prediction error understates the relevant prediction accuracy of the machine learning model. Specifically, we will primarily use the predictions from our model to compare outcomes with versus without the phase-out at the plant-month and plant-year levels. We therefore also evaluate the predictive performance of the model at these levels of aggregation. Specifically, Figure 1.6b plots predicted versus observed annual average operating rates. As the figure shows, the performance is substantially improved, with most of the observations clustered close to the 45 degree line, and the areas of systematic error largely disappear. The cross-validated out-of-sample R^2 rises to 0.96 and the mean-squared error falls to 0.004.

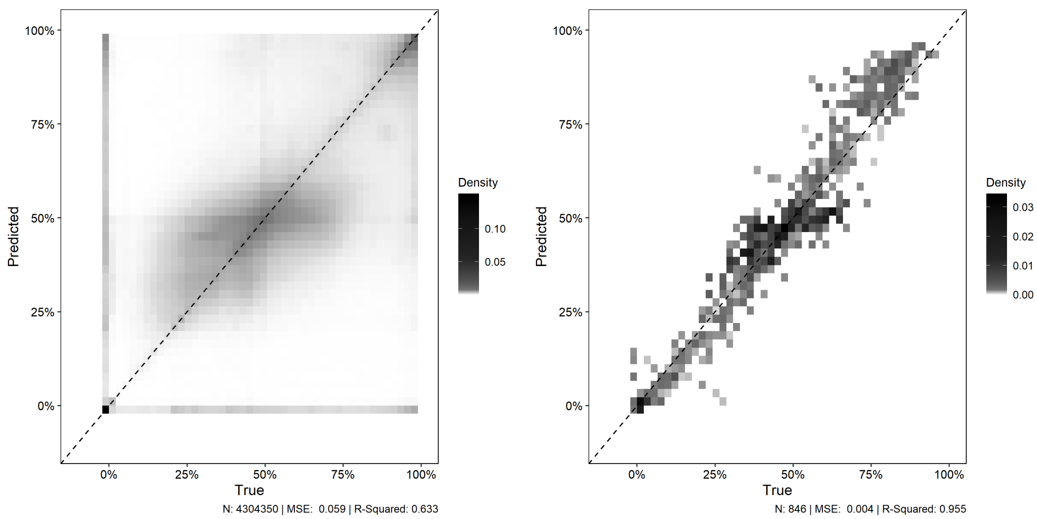
Lastly, our equivalent modeling to predict counterfactual hourly wholesale prices performs well with a cross-validated out-of-sample R^2 of 0.88. By far the most important predictor is the estimated marginal cost of the clearing plant. This makes sense as it is consistent with the core process by which prices are determined in the wholesale market.

1.3.2 Findings for Phase-Out Application

Figure 1.7 shows the median model predictions for how the nuclear phase-out impacted aggregate plant-level electricity production in Germany. As expected, points on this figure tend to lie above the horizontal axis; the nuclear phase-out reduced nuclear generation, with fossil-fuel-fired production filling

price-elastic, and the rates they pay are more responsive to changes in wholesale electricity prices. Still, even a relatively conservative assumption regarding the price-elasticity of these consumers is unlikely to produce an 8% change in demand based on the change in prices that is attributable to the phase-out.

Figure 1.6: Machine Learning Model Performance: Plant-Level Electricity Production



(a) Hourly Data *(b) Annual Data*

Notes: This figure illustrates the accuracy of the plant-level predictions from the machine learning model presented in Section 5. The model predicts the operating rate of each power plant in each hour, where a value of 0% means that a plant is offline and a value of 100% means that the plant is running at maximum capacity. Values on the 45 degree line indicate perfect accuracy, and we summarize this both visually and by computing measures of Mean Squared Error and R-Squared. We compute these metrics using out-of-sample five-fold cross-validation. Darker areas indicate higher numbers of plant-hour (or plant-year) observations. Each pixel represents the predicted vs. actual operating rate in increments of 2%. Panel (a) shows prediction accuracy at an hourly timescale. The number of observations is 4,304,350, and the MSE and R-square are 0.059 and 0.633, respectively. Panel (b) shows prediction accuracy after taking annual averages of our hourly predictions. The number of observations is 846, and the MSE and R-square are 0.004 and 0.955, respectively.

the gap. The largest response to the phase-out comes from the hard coal plants.

Figure 1.8 illustrates which plants and border points increased production to meet the reductions in nuclear output due to the phase-out. Most of the fossil-fuel generation comes from the industrial regions in the west and south of the country. Changes to net imports come primarily at the borders with Denmark, France and the Czech Republic.

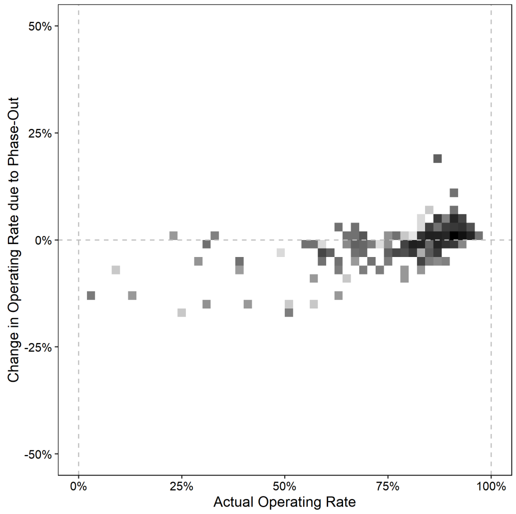
Finally, Figure 1.9 shows how the predicted changes to electricity generation vary across the different renewables scenarios we study. As expected, in the low renewables scenario the entirety of the difference in production has to come from additional fossil fuel-fired generation and changes to net imports. As the assumed response from renewables to the phase-out grows, a greater wedge of additional wind and solar production reduces the need for increases from fossil sources and net imports.

Interestingly, the scenarios with higher renewables also demonstrate the ability of the machine learning approach to capture important constraints in the dispatch of coal plants. This is clearest in the high renewables scenerio where net decreases in production at coal-fired plants is visible in later years. This almost certainly reflects the ramping constraints these plants face as the penetration of renewable production on the system grows.

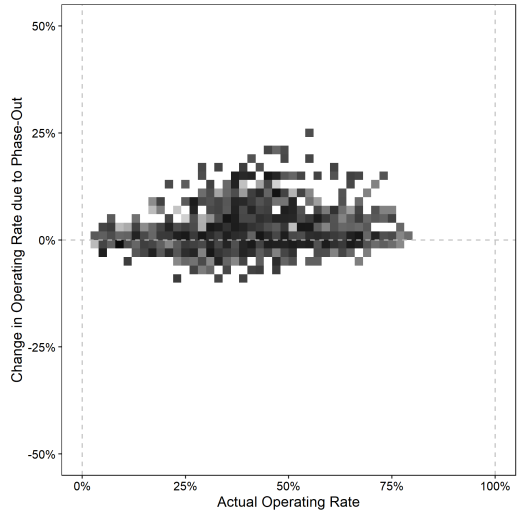
1.4 Conclusion

This chapter has set out a new application of machine learning methods to the study of electricity markets. It has also described an initial application to a policy evaluation of the phase-out of nuclear power in Germany. The results indicate this new approach has promise in that it can replicate many of the features of electricity markets that are of interest. This includes basic features like the dispatch of lower marginal cost plants ahead of higher marginal cost plants. However, the modeling results also demonstrate a capacity to capture more complex aspects of electricity market outcomes that are less readily dealt with using traditional simulation modeling tools. For instance, the simple inclusion of a dummy variable for combined heat and power is able to pick out many of the unique operational characteristics of these plants. Similarly, the ramping constraints faced by inflexible coal plants during periods of high renewables production also appear to be incorporated into the patterns picked out by the machine learning approach. There are undoubtedly improvements to be made, and additional tweaks necessary in each specific context, but the initial findings here are certainly encouraging.

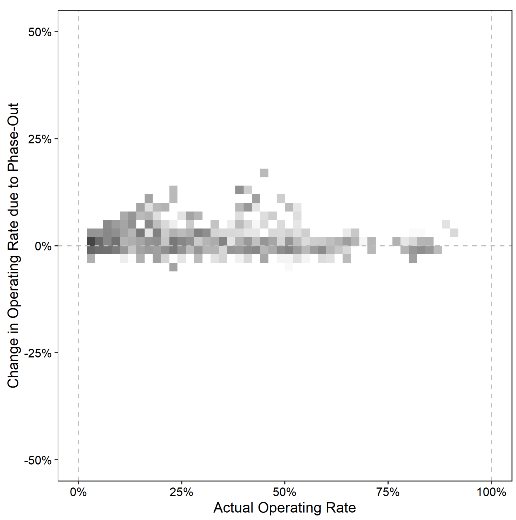
Figure 1.7: Plant-level Changes in Production due to the Phase-Out



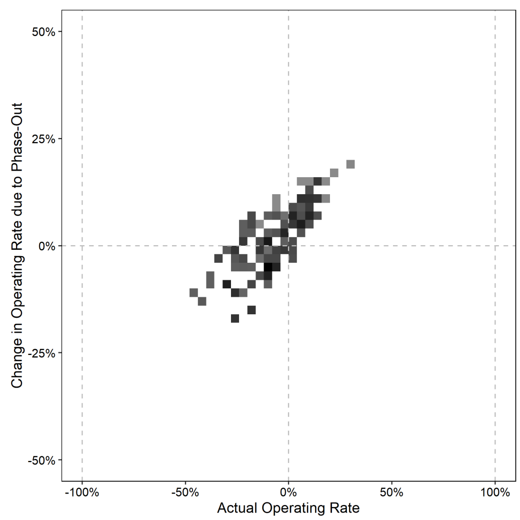
(a) Lignite



(b) Hard Coal



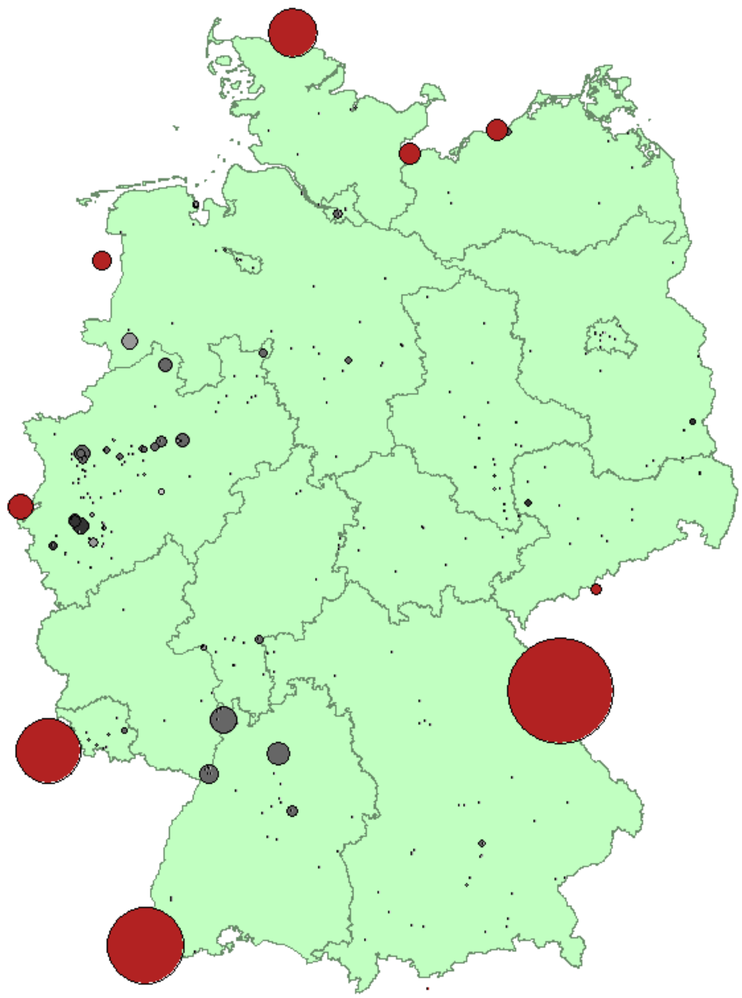
(c) Lignite



(d) Hard Coal

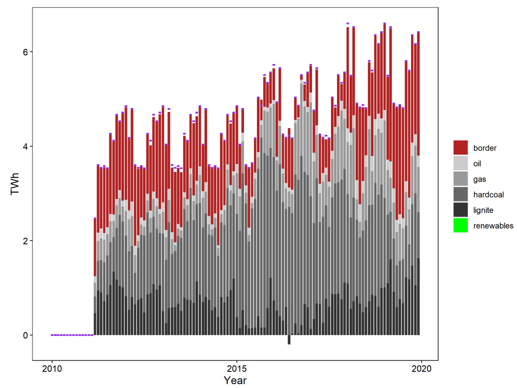
Notes: This figure illustrates the plant-level disaggregation of the machine learning prediction model results. The model predicts the operating rate of each power plant in each hour, where a value of 0% means the plant is offline and a value of 100% means it is running at maximum capacity. These figures plot plant-level annual average operating rates. The x-axis corresponds to each plant's operating rate in the baseline scenario with the phase-out. The y-axis corresponds to the impact of the phase-out on plant-level operations. This is determined by the difference between the predictions in the scenario with the phase-out versus the scenario without the phase-out. Darker areas indicate higher numbers of plant-year observations. Each panel refers to a different type of dispatchable electricity source. Panel (a) covers lignite plants, panel (b) covers hard coal plants, panel (c) covers gas plants and panel (d) covers border points. Oil plants are not shown because they are a very small portion of total capacity and are largely invariant to the phase-out.

Figure 1.8: Map of Plant-Level Changes in Production due to the Phase-Out

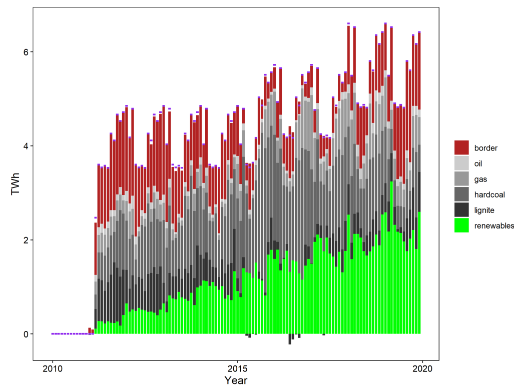


Notes: This map illustrates the location of the fossil-fuel-fired plants or border points that increased their electricity production as a result of the nuclear phase-out policy. The size of the circle reflects the amount of additional production provided by the fossil-fuel plant or border point. Points in red are border points and points in grey are fossil-fuel plants. Lignite plants are depicted in the darkest grey, followed by hard coal, then natural gas, and finally oil plants are depicted in the lightest grey.

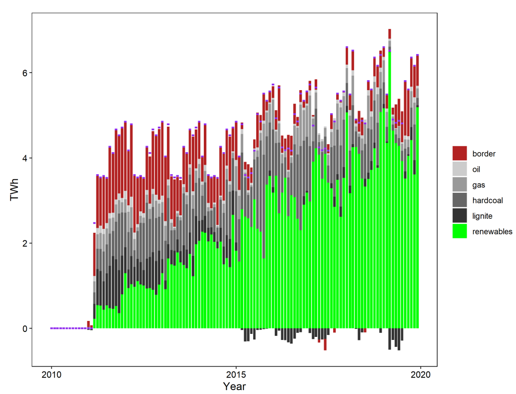
Figure 1.9: Estimated Impact of the Nuclear Phase-Out on Electricity Production by Renewables Scenario



(a) Low



(b) Central



(c) High

Notes: This figure plots the monthly difference between the predictions from our machine learning model with the phase-out minus without the phase-out. The start of the phase-out is in March 2011. Panel (a) reports the estimates for the low renewables scenario where there is no response from renewables investment to the phase-out. Panel (b) reports the estimates for the central renewables scenario where there is a 30 TWh per year increase in renewables production by 2020 due to the phase-out. Panel (c) reports the estimates for the high renewables scenario where there is a 60 TWh per year increase in renewables production by 2020 due to the phase-out.

Chapter 2

The Private and External Costs of the Phase-Out of Nuclear Power in Germany

2.1 Introduction

The Fifth Intergovernmental Panel on Climate Change Assessment Report (IPCC 2013) and the 21st United Nations Climate Change Conference ("COP21") have both recommended that nuclear power should be a part of the global solution to climate change. This is because nuclear electricity generation produces minimal carbon emissions under normal operating conditions (Markandya and Wilkinson, 2007). In contrast, burning fossil fuels to produce electricity is known to emit both global pollutants that contribute to climate change and local pollutants that have negative consequences on human health (NRC and NAS, 2010; Jaramillo and Muller, 2016; Deschenes, Greenstone and Shapiro, 2017; Holland et al., 2018). Despite this, many countries have substantially decreased the share of their electricity production from nuclear sources. For example, Belgium, Spain, and Switzerland all have policies in place to phase-out nuclear power entirely. This is due in large part to concerns about long-term solutions for storing nuclear waste and public fears of catastrophic nuclear accidents. These fears intensified considerably following the incidents at Three Mile Island in 1979, Chernobyl in 1986, and Fukushima in 2011.

The decision to phase-out nuclear production in many countries seems to suggest that the expected costs of nuclear power exceed the benefits. Yet, there remains considerable uncertainty about some of these costs and benefits as there is a glaring lack of empirical studies quantifying the *full* range of economic and environmental impacts from large-scale nuclear sector closures.

This paper presents a first attempt at filling this important gap by documenting the impact of the phase-out of nuclear power in Germany on multiple market and environmental outcomes. In particular we focus on the shutdown of eleven of the seventeen nuclear reactors in Germany that occurred between 2011 and 2019 following the Fukushima accident in Japan. This context affords us several advantages over previous research studying the impacts of nuclear power plants closures. First, and most importantly, Germany shut down over 8 GW of nuclear production capacity over a few months in 2011, representing close to a 5% reduction in total capacity. By 2019 this had increased to a total of 12.4 GW of closed nuclear production capacity. This is far larger than the reductions in capacity studied by previous research that focused on the shutdown of a small number of nuclear plants in the United States (Davis and Hausman, 2016; Severnini, 2017). Second, Germany plans to shut down all of its remaining nuclear reactors by 2022. Our study thus provides timely policy-relevant information on the consequences of Germany's nuclear phase-out moving forward. Third, studying electricity markets in the European context gives us the opportunity to examine how cross-border trade was impacted by a large shock to production in one country. Finally, Germany's nuclear phase-out was the direct result of political actions taken following extensive anti-nuclear campaigning in Germany as well as a sudden increase in the perceived risk of nuclear power following the Fukushima accident (Goebel et al., 2015). Importantly, the phase-out was not caused by changes in the economic or environmental conditions pertaining to nuclear production in Germany. This facilitates a causal interpretation of our analysis of the initial phase-out decision based on comparing the conditional averages of economic and environmental outcomes before versus after the nuclear phase-out.

This paper adds to the relatively small literature that explores the effects of the nuclear phase-out on the German electricity sector. For instance, both Traber and Kemfert (2012) and Knopf et al. (2014) used mixed economic-engineering models of the power sector to forecast changes to capacity investments, electricity prices and carbon emissions. More recently, Grossi, Heim and Waterson (2017) uses an event study framework to econometrically estimate the impact of the initial nuclear plant closures in 2011 on electricity prices over a three year window between 2009 and 2012. The broad consensus across this small existing literature is that nuclear power was replaced primarily by fossil fuel-fired production, resulting in higher electricity prices and more carbon emissions. However, by focusing on aggregate outcomes, the previous research ignores several important impact margins of the nuclear phase-out. Specifically, we show that much of the social cost of the switch from nuclear to fossil fuels is driven by changes in local air pollution concentration levels around individual power plants before versus after the phase-out.

This paper goes beyond the aggregate electricity sector by estimating the economic and environmental costs of the nuclear phase-out in Germany using rich plant-level data and ambient pollution monitor data. We contribute and expand on the existing literature in several important ways. First, our empirical analysis considers both the initial nuclear reactor closures in 2011 as well as the subsequent incremental shutdowns up until the end of 2019. Second, in addition to electricity prices and carbon emissions, we estimate the spatially disaggregated impacts of the phase-out on production costs, net electricity imports, and local air pollution. This is especially important because the increases in local air pollution as a consequence of shifting production from nuclear to coal represents the majority of the overall costs of the nuclear phase-out.

To proceed, we utilize a new machine learning framework to derive the appropriate counterfactual outcomes under a "no phase-out" scenario. We use our predicted changes in plant-level electricity production due to the nuclear shutdowns to calculate the costs of the shift away from nuclear power. We first show that the average operating cost per MWh of German electricity production increased as a consequence of the phase-out. This is unsurprising given that nuclear plants have lower marginal costs than fossil fuel-fired plants. In addition, we find that the switch from nuclear power to fossil fuel-fired production resulted in substantial increases in global and local air pollution emissions. Overall, we estimate that the social cost of the phase-out to German producers, residents, and non-residential consumers is around 3 billion euros per year. Even using alternative assumptions regarding the value of avoided health damages and the impact of the phase-out on the deployment of renewable power, the social costs still range from 1.4 to 8.7 billion euros per year. Consistently we find that the majority of this cost is due to the increased mortality risk from local air pollution exposure as a consequence of producing electricity by burning fossil fuels rather than utilizing nuclear sources. The majority of the cost of the phase-out is thus borne by German residents rather than producers or non-residential consumers of electricity.

The nuclear phase-out had benefits as well. In particular, shutting down nuclear plants avoids any operating costs associated with keeping these plants open and running. Shutdowns also reduce the risk of nuclear accidents and decrease the costs associated with storing nuclear waste (D'haeseleer, 2013; JECR, 2019). However, even the largest estimates of the benefits of the nuclear phase-out are unable to outweigh the substantial social costs we find. Moreover, consistent with previous work, we find that electricity prices in Germany are higher due to the phase-out. This increase in electricity prices results in increases in the profits earned by most electricity producers but imposes additional costs on German electricity consumers.[1]

Despite the substantial costs to German citizens, the nuclear phase-out still has widespread support. Specifically, more than 81% of German residents

[1] Neidell, Uchida and Veronesi (2019) similarly finds an increase in electricity prices due to the phase-out of nuclear power in Japan following the Fukishima accident. This phase-out-induced increase in prices resulted in a decrease in energy consumption, which in turn caused substantial increases in mortality during very cold temperatures.

were in favor of the phase-out in a 2015 survey (Goebel et al., 2015). Existing evidence suggests that the average person greatly overestimates the expected costs of a nuclear accident, both in terms of likelihood and number of fatalities (Slovic, Fischhoff and Lichtenstein, 1979; Slovic and Weber, 2002; Slovic, 2010). In addition, the health costs associated with local air pollution exposure may simply be less salient than the risk of a nuclear accident, especially after the Fukishima accident in Japan. Regardless of the underlying causes, widespread anti-nuclear sentiment around the world has made it difficult to set policy pertaining to nuclear power based solely on a dispassionate benefit-cost analysis.

This paper proceeds as follows. The next section provides background on the German electricity sector. In Section 2.2, we briefly recap the machine learning approach we use to estimate the impact of the phase-out on electricity production and prices. We also set out the approach we take to valuing the private and external costs and benefits of these changes. Section 2.3 presents our estimates of the economic and environmental impacts of the phase-out. Finally, we discuss the policy implications of our findings in Section 2.4.

2.2 Empirical Strategy

2.2.1 Estimating Changes to Generation, Net Imports and Prices due to the Phase-Out

The primary impacts of the phase-out are the reduction in nuclear electricity production, and the corresponding increase in production from alternative sources. We employ the machine learning approach set out in the previous chapter to estimate which alternative sources stepped in to fill the gap left by the shuttered nuclear plants. Specifically, our machine learning approach predicts which power plants increased their output in response to the nuclear plant closures. Any shift towards dirtier fossil fuel sources could be mediated by the potential scope for the phase-out to have incentivized additional investment in renewable energy sources such as wind and solar power. We therefore explore a range of scenarios to test the sensitivity of our findings to this. We also expand the approach to look at changes to electricity prices.

2.2.2 Estimating Private Costs

Costs are a combination of variable and fixed costs. Variable costs are the product of each plant's hourly production with our estimates of hourly marginal cost. We then add additional information on plant-level ongoing fixed costs. For fossil plants we take source-level assumptions for these from the US Energy

Information Administration. For nuclear plants we rely on a range of industry sources which indicate that the overall ongoing costs of existing nuclear plants are likely roughly €30/MWh. Renewable plants are assumed to have zero marginal costs. To account for the fixed operating and capital costs from renewables we rely on levelized cost values for wind and solar plants from the International Renewable Energy Agency. These values are specific to Germany and capture annual average changes in costs for plants built in each year.

We also account for a number of important differences in investment due to the phase-out policy. For nuclear plants Keppler (2012) argues that extending the lifetime of the nuclear reactors in Germany would have required investments of roughly €500 million per reactor, or €8.5 billion in total. These investment costs are avoided due to the nuclear phase-out. However, Knopf et al. (2014) argues that the phase-out led to 8GW of additional fossil-fuel-fired capacity being required by 2030. If we assume coal-fired capacity has capital costs of €3000/kW while gas-fired capacity has capital costs of €1000/kW, the total additional investment costs in fossil-fuel-fired capacity as a result of the nuclear phase-out range from €8-24 billion. Subtracting the avoided investment costs in nuclear from this range, the net investment costs of the phase-out are between -€0.5 billion to €16 billion. In the long-term then it seems plausible that the phase-out likely increased overall capital investment costs, particularly. We incorporate the portion of these additional investment costs that would likely have been incurred by the end of our sample period into our analysis of costs presented below. In general though these are small relative to the changes driven by shifts in marginal operating costs.

For reference we also calculate revenues and profits. Revenues are calculated as the product of plant-level production and wholesale electricity prices; we thus ignore any additional revenues plants may receive, such as capacity payments, ancillary services payments, subsidies etc. Profits are calculated as revenues minus costs. For net imports, we quantify revenues and costs as the net import of electricity multiplied by the wholesale price in the relevant neighboring country.[2] Note that because we do not account for revenues from subsidies, some sources will likely have negative profits. This particularly applies to renewable plants which derive a large portion of their revenues from subsidies.

[2]Our analysis implicitly assumes that the phase-out caused no change to the electricity prices of neighboring countries. Fully modeling electricity markets for each of these interconnected countries would entail a prohibitive amount of additional data collection. This additional modeling would also be unlikely to dramatically alter the overall findings given the dominant role of domestic production in meeting Germany's electricity demand. Finally, since prices in interconnected electricity markets likely increased due to the phase-out, our net import cost estimates are likely to be a lower bound.

2.2.3 Estimating External Costs Using Reported Emissions Rates

Our analysis of the environmental costs caused by burning fossil fuels to produce electricity combines data from multiple sources. The European Environment Agency (EEA) reports annual carbon dioxide emissions for each plant that participates in the EU ETS. The EEA also reports annual plant-level data on fuel inputs and local pollution emissions.[3]

First, we estimate the change in carbon emissions due to the phase-out. To proceed, we calculate the change in the amount of fuel burned by each plant associated with the phase-out impact on each plant's hourly production and using each plant's thermal efficiency (i.e.: how well the plant translates input heat energy to output electricity). We then use the carbon intensity of different fuels documented in industry reports to convert changes in fuel burned to changes in plant-level CO_2 emissions.[4]

We also estimate the change in local pollution emissions due to phase-out-induced changes in plant production levels. Similar to the approach for CO_2 emissions, we translate changes in fuel use into changes in emissions using plant-level emissions rates for each local pollutant from the EU Large Combustion Plant Directive (LCPD). The LCPD database provides annual plant-level data on fuel inputs and emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x) and particulate matter (PM). The LCPD data covers the vast majority of large fossil plants in Germany.[5] We assign the small number of plants not in the LCPD database an emissions factor based on the average emissions factor of plants with the same fuel type.

We next monetize the damages caused by CO_2 and local air pollution emissions. For CO_2, we monetize damages assuming a social cost of carbon of $\$50/tCO_2$. To assess the health damages from increases in local air pollution, we rely on two studies that estimate the health impacts of local pollution in Europe (EEA, 2014; Jones et al., 2018). In particular, Jones et al. (2018) provide estimates of the annual health damages from the local air pollution emitted by roughly four hundred of the largest coal-fired power plants in Europe. We use these data to convert our predicted increases in plant-level kilotons of SO_2, NO_x and PM emissions into monetized health damages.[6]

[3] These data are collected as part of monitoring for the EU Large Combustion Plant Directive.

[4] The carbon intensities we use are 93.6 tCO2/TJ for hard coal, 55.9 tCO2/TJ for gas and 74.0 tCO2/TJ for oil. We consider three different intensities for lignite depending on the mining region that the plant sources its coal from. These are 113.3 tCO2/TJ (Rhineland), 111.2 tCO2/TJ (Lusatian) and 102.8 tCO2/TJ (Central).

[5] Specifically, the data covers 99% of lignite capacity, 98% of hard coal capacity, 90% of gas capacity and 91% of oil capacity.

[6] Specifically, we assume that increased emissions at a given fossil-fuel-fired plant in Germany would have the same health damages as if they were emitted at the nearest location

2.2.4 Estimating External Costs Using Ambient Air Pollution Monitors

As an alternative to calculating damages using fuel inputs and reported emissions, we also compute damages using the estimated relationship between plant-level production and recorded air pollution at nearby monitoring stations. Station-level weather data comes from Germany's national meteorological service (DWD) and local pollution monitor data are from the German Environment Agency (UBA).

To do this we regress daily average local pollution concentration levels on daily unit-level electricity production. We focus on coal and oil fired electricity generating units in Germany over the sample period 1/1/2015-12/31/2019. For these regressions, we drop units that produce both heat and electricity (i.e.: combined heat and power plants). The unit of observation is a fossil fuel unit matched to an air quality monitor in a day-of-sample. All specifications include fixed effects for each unit/monitor pair as well as month-of-year fixed effects and year-of-sample fixed effects. We also further examine the robustness of our approach by including interactions with an indicator for whether the unit is upwind or downwind from the monitor. This should capture the way pollution will be dispersed from each source to nearby monitors according to the wind direction.

Table 2.1 presents the results from regressing daily average $PM_{2.5}$ concentration levels on daily unit-level electricity production. Table 2.2 repeats the analysis for NO2. As expected we find that increases in electricity production lead to increases in local air pollution concentrations. This increase remains positive and significant even after controlling for production at other nearby plants. The effect is also concentrated at monitors where the change in production is at a plant upwind from the monitor, which makes sense. However, these effects are only clear for $PM_{2.5}$, with the NO2 analysis less able to pick out an obvious distinction between upwind and downwind changes.

2.3 Results

This section presents the primary results on the full range of impacts of the nuclear phase-out over our entire 2010-2019 analysis period. Specifically, we compare the market and environmental outcomes with versus without the nuclear phase-out using the predictions from our machine learning model.

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for which we have health damages estimates. The mean distance between each of the power plants in our data set and closest of the 400 locations with damage estimates is 29km. The median is 14km. Jones et al. (2018) provides estimates for roughly 10% of the plants in our data-set, noting that these plants are among the 400 largest coal plants in Europe.

Table 2.1: Estimated Effect of Electricity Production on Ambient PM2.5 Concentration

Dependent Variable: PM2.5 in micrograms per cubic meter				
	(1)	(2)	(3)	(4)
Electricity Production (GWh)	0.178***	0.057***		
	(0.026)	(0.010)		
Upwind × Production (GWh)			0.115***	0.123***
			(0.016)	(0.016)
Downwind × Production (GWh)			0.013	-0.010
			(0.011)	(0.011)
Neither DW nor UW × GWh			0.051***	0.046***
			(0.010)	(0.009)
GWh from Other Plants		0.033***	0.030***	0.026***
		(0.004)	(0.003)	(0.003)
GWh from Other Upwind Plants			0.009***	0.009***
			(0.002)	(0.001)
GWh from Other Downwind Plants			-0.003*	-0.002**
			(0.001)	(0.001)
Distance Bandwidth	250	250	250	300
Unit/Monitor Pair FE	Yes	Yes	Yes	Yes
Month-of-Year FE and Year FE	Yes	Yes	Yes	Yes
Month-of-Sample FE	No	No	No	No
Number of Obs.	2,341,993	2,341,993	2,341,993	3,108,471

Notes: This table presents the results from regressing daily average $PM_{2.5}$ concentration levels on daily unit-level electricity production. We focus on coal and oil fired electricity generating units in Germany over the sample period 1/1/2015-12/31/2019; for these regressions, we drop units that produce both heat and electricity (i.e.: combined heat and power plants). The unit of observation is a fossil fuel unit matched to an air quality monitor in a day-of-sample. Standard errors, reported in parentheses, are two-way clustered by unit/monitor pair and month-of-sample. For Columns 1-3, we consider all units within 250km of the air quality monitor; Column 4 focuses on all units within 300km of the air quality monitor. All specifications include fixed effects for each unit/monitor pair as well as month-of-year fixed effects and year-of-sample fixed effects. In Column 1, we regress the daily average $PM_{2.5}$ on electricity production from the unit (in GWh) with no additional controls. In Column 2, we regress $PM_{2.5}$ on unit-level generation controlling for the production from all other units within the relevant distance bandwidth. The specifications in Columns 3-4 instead include generation interacted with an indicator for whether the unit is upwind from the monitor, generation interacted with an indicator for whether the unit is downwind from the monitor, and generation interacted with an indicator for whether the unit is neither upwind nor downwind from the monitor. The regressions presented in Columns 3-4 additionally include total generation from other units within the bandwidth, total generation from other units in the distance bandwidth that are upwind from the monitor, and total generation from other units in the distance bandwidth that are downwind from the monitor.

Table 2.2: Estimated Effect of Electricity Production on Ambient NO2 Concentration

Dependent Variable: NO2 in micrograms per cubic meter				
	(1)	(2)	(3)	(4)
Electricity Production (GWh)	0.340***	0.102***		
	(0.031)	(0.009)		
Upwind × Production (GWh)			0.107***	0.099***
			(0.012)	(0.011)
Downwind × Production (GWh)			0.105***	0.087***
			(0.011)	(0.010)
Neither DW nor UW × GWh			0.098***	0.077***
			(0.009)	(0.008)
GWh from Other Plants		0.063***	0.059***	0.050***
		(0.003)	(0.003)	(0.002)
GWh from Other Upwind Plants			0.008***	0.008***
			(0.001)	(0.001)
GWh from Other Downwind Plants			0.006***	0.004***
			(0.001)	(0.001)
Distance Bandwidth	250	250	250	300
Unit/Monitor Pair FE	Yes	Yes	Yes	Yes
Month-of-Year FE and Year FE	Yes	Yes	Yes	Yes
Month-of-Sample FE	No	No	No	No
Number of Obs.	6,578,216	6,578,216	6,578,216	8,557,854

Notes: This table reports estimates from regressions of daily average NO_2 concentration levels on daily unit-level electricity production. We focus on coal and oil fired electricity generating units in Germany over the sample period 1/1/2015-12/31/2019; for these regressions, we drop units that produce both heat and electricity (i.e.: combined heat and power plants). The unit of observation is a fossil fuel unit matched to an air quality monitor in a day-of-sample. Standard errors, reported in parentheses, are two-way clustered by unit/monitor pair and month-of-sample. For Columns 1-3, we consider all units within 250km of the air quality monitor; Column 4 focuses on all units within 300km of the air quality monitor. All specifications include fixed effects for each unit/monitor pair as well as month-of-year fixed effects and year-of-sample fixed effects. In Column 1, we regress the log of daily average NO_2 on electricity production from the unit (in GWh) with no additional controls. In Column 2, we regress NO_2 on unit-level generation controlling for the production from all other units within the relevant distance bandwidth. The specifications in Columns 3-4 instead include generation interacted with an indicator for whether the unit is upwind from the monitor, generation interacted with an indicator for whether the unit is downwind from the monitor, and generation interacted with an indicator for whether the unit is neither upwind nor downwind from the monitor. The regressions presented in Columns 3-4 additionally include total generation from other units within the bandwidth, total generation from other units in the distance bandwidth that are upwind from the monitor, and total generation from other units in the distance bandwidth that are downwind from the monitor.

2.3.1 Changes to Generation, Net Imports and Prices due to the Phase-Out

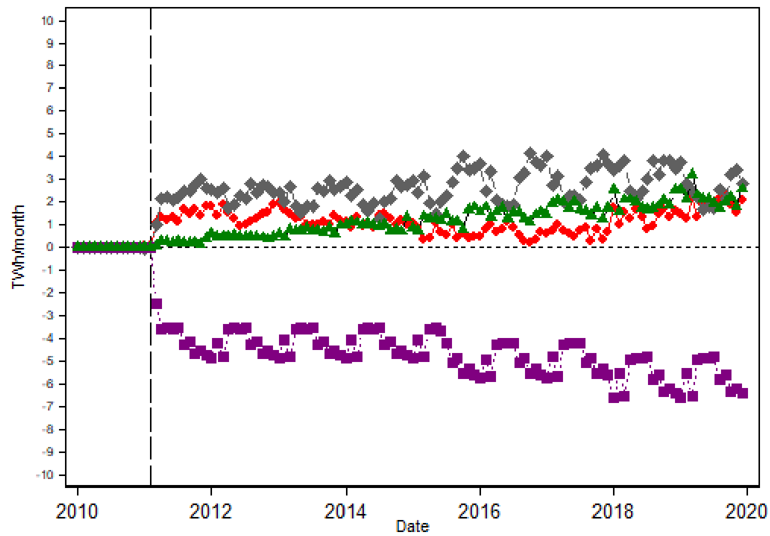
Figure 2.1 presents our estimates of the aggregate impact of the nuclear phase-out on electricity production and wholesale prices. First among these is Figure 2.1a, which reports the monthly average difference in predicted production and net imports (in TWh) with minus without the phase-out policy. We report monthly average differences in fossil-fired electricity production (grey diamonds), net imports (red circles), renewable electricity production (green triangles) and nuclear electricity production (purple squares). The start of the nuclear phase-out in March 2011 is marked by the vertical black dashed line. By construction, we find a stark reduction in total nuclear production of 4 TWh per month after this point, rising to 6 TWh per month as additional plants close throughout the period. The cyclicality of this impact is due primarily to the fact that nuclear reactors typically schedule their maintenance and refuelling outages in the summer months.

In our baseline scenario we assume that at least some of this lost nuclear production was replaced by accelerated investment in renewable sources as a direct response to the phase-out. This can be seen in the steady rise of additional renewable electricity production, with 2.5 TWh per month expected 2020, again by construction. Our machine learning analysis then estimates the remaining contribution of various dispatchable sources. Here we see the phase-out caused a large increase in fossil-fuel-fired electricity production of 2-3 TWh per month, as well as a smaller increase in net imports of electricity of around 1 TWh per month. Importantly, all of these changes are calculated after taking into account any overall trends that were occurring independent of the phase-out policy. This includes the large rise in renewable energy production over this period. Another notable result in Figure 2.1a is that the stark increase in fossil production starting in March 2011 persists over our entire sample period.

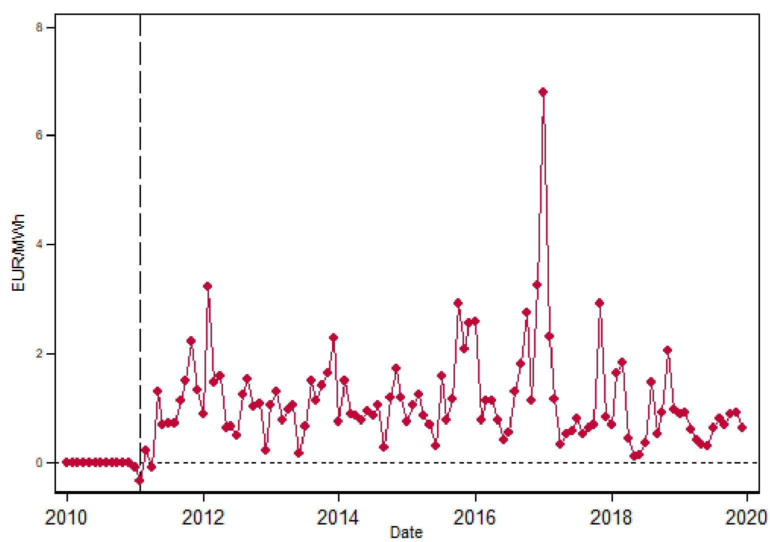
Figure 2.1b is constructed similarly and reports the impact of the nuclear phase-out on wholesale electricity prices in Euros per MWh. The estimates show that the phase-out resulted in an increase in wholesale prices of around 1 euro per MWh. Another key result in Figure 2.1b is that the increase in wholesale prices persists through the end of 2019, as was similarly noted for fossil fuel electricity production. Finally, the figure also shows that the phase-out may have exacerbated episodic increases in prices, such as the large price spike in January 201 due to an unusual cold spell in Europe (European Commission, 2017).

Table 2.3 further summarizes these findings. Column (1) complements the information in Figure 2.1 by reporting annual average predicted wholesale electricity price and electricity production in the scenario with the phase-out. Column (2) reports these predicted outcomes for the scenario without the phase-out. Column (3) reports the difference between the first two columns

Figure 2.1: Estimated Impact of the Nuclear Phase-Out on Electricity Production and Prices



(a) Electricity Production



(b) Wholesale Electricity Prices

Notes: This figure plots the monthly difference between the predictions from our machine learning model with the phase-out minus without the phase-out. The start of the phase-out in March 2011 is marked by the vertical black dashed line. Panel (a) reports the estimates for all fossil-fuel-fired electricity production (grey diamonds), net imports (red circles), renewable electricity production (green triangles), and nuclear production (purple squares). Panel (b) presents the change in wholesale electricity prices.

Table 2.3: Estimated Impact of the Nuclear Phase-Out on Wholesale Electricity Prices, Electricity Production by Source, and Net Imports

	Average with Phase-Out (1)	**Average without Phase-Out (2)**	**Change (3)**	**Change (%) (4)**
Production ($^{\text{TWh}}/_{\text{Year}}$)	477.1	472.7	4.4	0.9
Nuclear	82.7	139.1	-56.4	-40.5
Lignite	155.0	148.6	6.4	4.3
Hard Coal	99.7	82.6	17.1	20.7
Gas	37.2	30.8	6.4	20.8
Oil	9.7	7.9	1.8	22.8
Net Electricity Imports	-18.1	-32.1	14.0	-43.6
Wind + Solar	110.9	95.9	15.0	15.6
Wholesale Prices ($^{\text{Euros}}/_{\text{MWh}}$)	39.4	38.2	1.2	3.1

Notes: This table reports annual average electricity production by type and wholesale electricity prices with versus without the nuclear phase-out, as estimated using our machine learning algorithm. These annual averages are calculated using data spanning from immediately after the phase-out in March 2011 to the end of 2019.

and Column (4) provides this estimated effect as a percentage by dividing column (3) by column (1). The estimates reveal that the phase-out caused inflation-adjusted wholesale electricity prices to increase by €1.2 per MWh on average, a 3.1% increase relative to the prices that would have prevailed if the phase-out had not occurred. Consistent with Figure 2.1a, nuclear production fell by an average of 56.4 TWh per year during the phase-out period, corresponding to a 40.5% decline. The next rows decompose the previously documented increase in fossil production by source. The largest increases, both in absolute and percentage terms, are from hard coal and gas-fired production. Specifically, annual average production from hard coal increased by 17.1 TWh (20.7%) while gas-fired production increased by 6.4 TWh (20.8%). Finally, the phase-out caused net imports to increase by 14.0 TWh per year on average. In sum, the 2011 phase-out lead to large changes to Germany's electricity generation mix.

2.3.2 Private Costs and Benefits of the Phase-Out

Table 2.4 examines the impact of the nuclear phase-out on financial outcomes for power plants, once again organized by plant fuel type. We report predicted annual average revenues, costs, and profits. Revenues are calculated as the product of plant-level production and wholesale electricity prices; we thus ignore any additional revenues plants may receive, such as capacity payments, ancillary services payments, subsidies etc.

Table 2.4: Estimated Impact of the Nuclear Phase-Out on Revenues, Operating Costs, and Operating Profits

	Average with Phase-Out	**Average without Phase-Out**	**Change**	**Change (%)**
	(1)	**(2)**	**(3)**	**(4)**
Revenues ($\frac{\textbf{Bn. Euros}}{\textbf{Year}}$)	19.30	18.54	0.76	4.10
Nuclear	3.35	5.46	-2.11	-38.67
Lignite	6.27	5.82	0.45	7.73
Hard Coal	4.05	3.27	0.78	23.84
Gas	1.53	1.22	0.31	25.40
Oil	0.39	0.31	0.08	26.12
Net Electricity Imports	-0.68	-1.22	0.54	-44.32
Wind + Solar	4.37	3.68	0.69	18.75
Costs ($\frac{\textbf{Bn. Euros}}{\textbf{Year}}$)	33.17	31.98	1.19	3.72
Nuclear	2.51	4.61	-2.10	-45.53
Lignite	5.30	5.09	0.22	4.33
Hard Coal	4.72	4.11	0.60	14.59
Gas	2.41	2.09	0.32	15.32
Oil	1.39	1.14	0.25	21.96
Net Electricity Imports	-0.90	-1.48	0.58	-39.30
Wind + Solar	17.74	16.42	1.32	8.04
Profits ($\frac{\textbf{Bn. Euros}}{\textbf{Year}}$)	-13.88	-13.44	-0.44	3.27
Nuclear	0.84	0.84	-0.01	-1.18
Lignite	0.97	0.74	0.24	32.60
Hard Coal	-0.66	-0.84	0.18	-21.45
Gas	-0.88	-0.87	-0.01	1.15
Oil	-1.00	-0.83	-0.17	20.43
Net Electricity Imports	0.22	0.26	-0.04	-15.53
Wind + Solar	-13.37	-12.74	-0.63	4.95

Notes: This table reports average annual operating revenues, costs and profits with versus without the nuclear phase-out, as estimated using our machine learning algorithm. All values are annualized averages based on predictions from after the nuclear shutdowns in March 2011 to the end of 2017. Operating revenues are the product of each plant's hourly production with the hourly wholesale electricity price. We ignore any additional revenues plants may receive, such as capacity payments, ancillary services payments, subsidies etc. Operating costs are the product of each plant's hourly production with its hourly marginal cost. Operating profits are operating revenues minus operating costs. Other sources such as renewables are excluded from this table as we avoid making explicit assumptions about their marginal costs or their revenues (e.g., additional non-market subsidies).

The nuclear phase-out had a large effect on the revenues and profits of the firms that owned the nuclear plants that were shut down. Specifically, annual average revenues across all nuclear plants declined by \$2.1 billion per year. Annual average profits earned by nuclear plants did not fall after accounting for the reactor extension investments that plants would have had to make in the no phase-out scenario.

The revenues previously earned by the shut-down nuclear plants were primarily redistributed to fossil plants, most notably hard coal and natural gas plants. This shift occurred at a less than one-for-one ratio since nuclear plants have a much lower operating costs per MWh than fossil plants. Despite this, annual average operating profits at fossil plants increased by roughly \$0.24 and \$0.18 billion due to the phase-out at lignite and hard coal plants respectively. Profits at natural gas plants were largely unchanged.

The redistribution of profits amongst electricity producers has interesting implications for the political economy surrounding the phase-out policy. In particular, the four large firms that owned nuclear plants in Germany clearly opposed the policy both privately and publicly. However, there are two important factors that may have tempered their opposition. First, these firms would have been allowed to operate their nuclear plants into the 2030s only if they paid a nuclear fuel tax. This nuclear fuel tax would have taxed away a large portion of the inframarginal rents that these nuclear plants earn. Second, the four firms that owned nuclear plants also had large fossil plant portfolios both in Germany and across Europe. As we have seen, these fossil plants earned larger profits due to the nuclear phase-out, which likely cushioned any reduction in profits earned by the four firms as a result of the nuclear closures.

2.3.3 External Costs and Benefits of the Nuclear Phase-Out

External Costs of Changes to Local Pollution Emissions

This subsection presents two separate analyses of environmental costs associated with the phase-out-induced increase in fossil-fuel-fired production documented in the previous subsection. Specifically, burning fossil fuels emits both global pollutants such as carbon dioxide that contribute to climate change and local pollutants that adversely impact the health of exposed populations.

Table 2.5 presents the results of this analysis. Specifically, this table reports the fuel-specific annual emissions for CO_2 (in Megatonnes, Mt) as well as the emissions of three local pollutants: SO_2, NO_x, and PM (in kilotonnes, kt). Lignite and hard coal are by far the two largest polluters, contributing more than 90% of emissions. Lignite and hard coal also contribute the most in terms of monetary damages from emissions.

Table 2.5: Estimated Impact of the Nuclear Phase-Out on CO_2 Emissions and Local Air Pollution Mortality Damages

	Average with Phase-Out (1)	**Average without Phase-Out (2)**	**Change (3)**	**Change (%) (4)**
CO_2 Emissions ($\frac{\text{Mt}}{\text{Year}}$)	267.4	244.7	22.7	9.3
Lignite	177.1	169.8	7.4	4.4
Hard Coal	90.2	74.9	15.3	20.4
SO_2 Emissions ($\frac{\text{Kt}}{\text{Year}}$)	132.8	122.2	10.5	8.6
Lignite	91.7	88.3	3.4	3.9
Hard Coal	41.0	33.9	7.1	20.9
NO_x Emissions ($\frac{\text{Kt}}{\text{Year}}$)	174.7	160.2	14.5	9.0
Lignite	117.7	112.8	4.9	4.3
Hard Coal	57.0	47.4	9.6	20.3
PM Emissions ($\frac{\text{Kt}}{\text{Year}}$)	4.9	4.5	0.4	8.9
Lignite	3.2	3.1	0.1	3.2
Hard Coal	1.7	1.4	0.3	21.6
Mortality ($\frac{\text{Excess Deaths}}{\text{Year}}$)	7,069.8	6,369.0	700.9	11.0
Lignite	4,005.8	3,840.8	165.0	4.3
Hard Coal	3,064.1	2,528.2	535.9	21.2
Pollution Damages ($\frac{\text{Bn. Euros}}{\text{Year}}$)	18.31	16.49	1.82	11.03
Lignite	10.37	9.95	0.43	4.32
Hard Coal	7.94	6.55	1.39	21.23

Notes: This table reports estimates for emissions of CO_2 as well as three local pollutants: SO_2, NO_x, and PM. The final row presents estimates of the mortality damages from all three of these local air pollutants. All values are annualized averages based on predictions from immediately after the March 2011 to the end of 2017. Emissions are the product of each plant's hourly generation with our estimate of their emissions rate. Emissions rates are the product of (a) the amount of fuel required to produce one unit of electricity, and (b) the emissions intensity of the fuel. Emissions estimates are limited to fossil-fuel-fired plants in Germany. We ignore other potential sources of emissions in the electricity sector, such as emissions from smaller biomass, landfill gas or waste plants. We also focus on emissions and damages in Germany and so do not estimate changes in emissions in neighboring countries due to changes in net imports. For the pollution damages reported in the last row of the table, we present only the monetary costs associated with premature mortality due to air pollution exposure in order to ensure consistency with the complementary analysis using pollution monitor data.

In aggregate, the phase-out led to an increase in CO_2 emissions of 22.7 Mt per year. This corresponds to a 9.3% increase relative to the scenario without the nuclear phase-out. This increase in CO_2 emissions was primarily attributable to an increase in emissions from hard coal plants, with lignite and gas making up the remainder. Valuing these carbon emissions at a social cost of carbon of €50/tCO2 would mean the phase-out resulted in climate change damages of €1.1 billion per year. However, when considering that the German power sector is part of the EU ETS, the increase in carbon emissions in Germany must have been offset by reductions in carbon emissions elsewhere in Europe in order to meet the cap. As such we do not include these climate damage costs in our final estimate of the costs of the phase-out.

The phase-out also led to a roughly 9% increase in the emissions of each the three local air pollutants we consider (SO_2, NO_x, and PM). Again, this increase is due primarily to increased emissions from hard coal plants. The bottom panel of Table 2.5 reports annual average mortality damages summed across all three local air pollutants. From 2010-2019, local pollution emissions from fossil plants were responsible for around €18 billion in mortality costs each year. €1.8 billion of this annual mortality cost can be attributed to the nuclear phase-out, representing an 11% increase in damages relative to the scenario without the nuclear phase-out.[7] Put another way, the phase-out resulted in around 700 additional deaths per year from increased concentrations of SO_2, NO_x, and PM. The increase in production from hard coal plants is again the key driver here, making up roughly 80% of the increase in mortality impacts.

Given the importance of these health impacts to our analysis, we also use a secondary approach to value the costs imposed by increased local air pollution. This uses pollution monitor data to examine how changes in generation are linked to changes in ambient air pollution concentrations. We then calculate the increase in premature mortality due to any increase in air pollution concentrations using dose-response estimates from the ESCAPE project (Beelen et al., 2014).[8]

[7] We use a Value of Statistical Life of €2.56 million for Germany in line with Jones et al. (2018). We also examine a higher value of €6.7 million taken from Viscusi and Masterman (2017) as this is more in line with the approach taken by the US EPA.

[8] The European Study of Cohorts for Air Pollution Effects (ESCAPE) is one of the few studies on the health impact of air pollution exposure in Europe. It is based on 22 European cohort studies with a total study population of more than 350,000 participants. Specifically, the ESCAPE project reports that mortality rate when $PM_{2.5}$ exposure is X + 5 micrograms per cubic meter divided by the mortality rate when $PM_{2.5}$ exposure is X micrograms per cubic meter is 1.07. The corresponding hazard ratio for a 10 micrograms per cubic meter increase in NO_2 is 1.01. Based on these hazard ratios, we can calculate the increase in mortality caused by the additional air pollution due to the phase-out using the following formula:

$$VSL \times POP \times MR \times \left(1 - \frac{1}{\exp(\rho_j \Delta POLL_j)}\right) \tag{2.1}$$

for j=$PM_{2.5}$ or NO_2. POP and MR are the population and mortality rate in the exposure

Table 2.6: Impact of the Phase-Out on Local Air Pollution Mortality Damages

	Average with Phase-Out	**Average without Phase-Out**	**Change**	**Change (%)**
	(1)	**(2)**	**(3)**	**(4)**
NO_2 Concentrations ($\frac{\text{micrograms}}{\text{cubic meter}}$)	26.9	26.9	0.05	0.19
Lignite	24.6	24.6	0.03	0.12
Hard Coal	29.3	29.2	0.06	0.21
$PM_{2.5}$ Concentration ($\frac{\text{micrograms}}{\text{cubic meter}}$)	14.5	14.5	0.02	0.14
Lignite	15.5	15.5	0.01	0.06
Hard Coal	13.6	13.6	0.03	0.22
Mortality ($\frac{\text{Excess Deaths}}{\text{Year}}$)			367.8	
Lignite			101.1	
Hard Coal			266.8	
Pollution Damages ($\frac{\text{Bn. Euros}}{\text{Year}}$)			0.99	
Lignite			0.27	
Hard Coal			0.72	

Notes: This table reports estimates of the monetary damages associated with the premature mortality resulting from the additional air pollution exposure as a consequence of the nuclear phase-out. The changes in daily concentrations of $PM_{2.5}$, PM_{10}, and NO_2 are obtained by panel regressions of air pollution at the monitor-level on daily, plant-level electricity production; these regressions include plant fixed effects, month-of-year fixed effects and year-of-sample fixed effects. The coefficients from these regressions give us an estimated relationship between electricity production and pollution concentration levels for each pollutant and each fuel type. We multiply the relevant estimated relationship by our predicted changes in production by each plant due to the phase-out. The resulting changes in air pollution concentrations are converted to a change in premature mortality using dose-response estimates from the ESCAPE project (Beelen et al., 2014). We monetize this additional premature mortality using a value of statistical life of €2.56 million for Germany. We do not report the absolute levels of mortality or damages, only the change due to the phase-out, because the baseline levels of pollution recorded at monitors are not attributable entirely to power plant activity; for example, industrial facilities, cars, and trucks also emit these pollutants.

The estimates of monetized mortality damages are reported in Table 2.6. Specifically, we present the annual average impact of the phase-out on pollution concentrations, premature mortality and the monetized damages from this premature mortality. A few key results emerge. First, there is again clear evidence that the phase-out resulted in an increases in local pollution that in turn led to increases in premature mortality. Second, the changes in $PM_{2.5}$ and PM_{10} concentration levels due to the phase-out were responsible for much larger health impacts than the change in NO_2 air pollution (about 10 times more). Finally, the primary drivers of excess mortality are the hard coal and lignite power plants. The estimates in column (3) suggest that the phase-out resulted in just under 400 hundred additional excess deaths per year, amounting to €1 billion in annual damages.

Taken together, the results in Tables 2.5 and 2.6 paint a consistent picture of the monetized mortality damages attributable to the nuclear phase-out. That being said, our preferred estimate is the €1.8 billion per year in damages calculated based on reported emissions (Table 2.5). This is because the analysis using reported emissions considers a more complete set of pollutants and implicitly draws on a more sophisticated analysis of pollution transport and exposure. The results presented in Table 2.6 based on our estimated relationships between pollution concentrations and electricity production (Table 2.6) serves as a valuable complementary validation exercise, especially given it was derived using an entirely distinct approach. Lastly, we want to emphasize that the air pollution costs of the phase-out are economically sizable, amounting to a roughly 10% increase in damages from premature mortality due to air pollution emissions from Germany's power sector.

External Benefits due to Reduced Risk from Nuclear Accidents and Waste Storage

Nuclear power plants emit virtually no global or local air pollution. However, nuclear energy does come with catastrophic accident risk and requires storing the waste that results from nuclear production, which has important costs as well. For instance, JECR (2019) estimates that the cost of the Fukushima accident over the next forty years is between 35-80 trillion yen ($330-750 billion). Most of this cost will not be incurred by the firm that owned the Fukishima nuclear power plant; the costs of the Fukishima accident are largely borne by Japanese society as a whole.

More generally, estimates from the literature suggest that the external costs of nuclear power due to waste storage and accident risk fall between €1-4 per MWh (D'haeseleer, 2013). This wide range is due to differing estimates of accident probabilities and severity, as well as varying assumptions on discount

group. The parameter ρ_j corresponds to the hazard ratios described above and $\Delta POLL_j$ is the change in ambient air pollution caused by the phase-out for air pollutant j.

Table 2.7: Overall Estimated Impact of the Nuclear Phase-Out on Total Costs

	Average with Phase-Out (1)	**Average without Phase-Out (2)**	**Change (3)**	**Change (%) (4)**
Total Costs ($^{\$bn}/_{\textbf{Year}}$)	53.7	50.6	3.0	5.9%
	Private Costs			
Costs	33.2	32.0	1.19	3.7%
	External Costs			
Local Pollution Mortality				
Method 1: Reported Emissions	18.3	16.5	1.82	11.0%
Method 2: Pollution Monitors	–	–	0.99	–
Local Pollution Morbidity	1.9	1.6	0.13	9.9%
Nuclear Waste and Accidents	0.25	0.42	-0.17	-40.7%

Notes: This table reports the estimates of the different intensive margin costs incurred with versus without the phase-out. Private costs are the operating costs of the power plants in our analysis plus any changes in net imports (valued at the electricity price). We assume that the production costs of renewable and other sources are equal to zero when calculating these operating costs. External costs consist of climate damages from carbon emissions, mortality and morbidity costs from air pollution emissions, as well as the costs associated with nuclear accident risk and nuclear waste disposal. For the total costs row in bold, we use the estimates from the reported emissions method when adding in the external costs of local pollution on mortality.

rates. If we value the external costs of nuclear power at €3 per MWh, the expected benefits from the nuclear phase-out are very small at just €0.2 billion per year.

2.3.4 Total Costs and Benefits of the Nuclear Phase-Out

This subsection bring the analysis together by summarizing the full range of private and external costs and benefits of the nuclear phase-out. The private costs of the phase-out consist of changes in the operating costs of the power plants in our sample as well as any net costs from changes to imports and exports. The external costs of the phase-out include the monetized climate change damages from carbon emissions, the damages from mortality, and morbidity caused by the air pollution attributable to the change in electricity production mix. Finally, the benefits of the phase-out consist of reductions in the costs associated with nuclear waste and accident risks.

Table 2.7 reports the aggregate cost and benefits of the phase-out. The phase-out resulted in replacing low cost nuclear production with higher cost sources such as fossil fuels and net imports; this increases average operating costs in Germany by €1.2 billion per year. Whilst not trivial, these private costs are smaller than the external costs associated with the phase-out. Specifically, burning fossil fuels to produce electricity rather than using nuclear plants emits global pollutants such as CO_2 as well as local pollutants such as $PM_{2.5}$, SO_2 and NO_2. Overall we estimate the annual costs of the nuclear phase-out as approximately €3 billion per year.

Robustness Checks

Three key assumptions play a key role in our estimates: (a) the extent to which renewables investment increased due to the phase-out, (b) the Value of Statistical Life (VSL) used to monetize the additional mortality due to phase-out-induced local air pollution, and (c) the external costs of nuclear waste and accident risks. To explore the sensitivity of our findings to these parameters we conduct a number of robustness checks using alternative values.

Our central estimate is €2.56 million. We also examine the impact of using an alternative VSL of €6.7 million, taken from Viscusi and Masterman (2017). This is more in line with the approach taken by the US EPA. Viscusi and Masterman (2017) also discusses the shortcomings of the lower VSL we use in our analysis, which comes from analysis by the OECD. Switching to this higher VSL naturally increases the external costs of the phase-out by a factor of three. This suggests the external costs from health damages due to local air pollution could plausibly be €5.4 billion per year.

Similarly, the high degree of uncertainty in the external costs associated with nuclear waste and nuclear accident means that we explore parameters spanning an order of magnitude above and below our central assumed value of €3 per MWh. The resulting upper end value of €30 per MWh is 10 times larger than the external costs of nuclear power estimated in previous studies (D'haeseleer, 2013). This extremely conservative (i.e.: high) estimate increases the benefits of the phase-out from €0.2 billion per year to €2 billion per year. Even in this case the expected benefits from the nuclear phase-out are still unlikely to larger than the other social net costs, which consistently exceed €2 billion per year.

Lastly, we also examine three scenarios for renewables investment in response to the phase-out. Our central case has 30TWh per year of additional renewables by 2020. In the low renewables case we assume no additional renewables investment due to the phase-out. This scenario increases external costs because fossil fuel fired production plays a greater role in substituting for the lost nuclear output. However, the reduced investment in costly renewables lowers private costs, and so the change to overall net costs is negligible. The reverse is the case for the high renewables scenario where we assume 60TWh per year of additional renewables by 2020. By the end of our analysis period this is almost enough to entirely replace the lost nuclear production. As such any increase to external costs from local pollution is minimal in this scenario. However, the additional investment costs for renewables are substantial and so again, the overall net costs of the phase-out are broadly in line with our central scenario.

Taking these various sensitivities together we find that the net social costs of the phase-out range from €1.4 to €8.7 billion per year, with the largest source of any changes being the change to the assumed VSL.

2.4 Conclusions

Following the Fukashima disaster in 2011, German authorities made the unprecedented decision to: (1) immediately shut down almost half of the country's nuclear power plants and (2) shut down all of the remaining nuclear power plants by 2022. We quantify the full extent of the economic and environmental costs of this decision. Our analysis indicates that the phase-out of nuclear power comes with an annual cost to Germany of roughly $12 billion per year. Over 70% of this cost is due to the 1,100 excess deaths per year resulting from the local air pollution emitted by the coal-fired power plants operating in place of the shutdown nuclear plants. Our estimated costs of the nuclear phase-out far exceed the right-tail estimates of the benefits from the phase-out due to reductions in nuclear accident risk and waste disposal costs.

Moreover, we find that the phase-out resulted in substantial increases in the electricity prices paid by consumers. One might thus expect German citizens to strongly oppose the phase-out policy both because of the air pollution costs and increases in electricity prices imposed upon them as a result of the policy. On the contrary, the nuclear phase-out still has widespread support, with more than 81% in favor of it in a 2015 survey (Goebel et al., 2015). This support cannot be chalked up to a lack of concern regarding climate change. Indeed, German citizens widely support the transition to renewables as part of the Energiewende program even though the costs of this transition were €26 billion in 2017 alone. German citizens are also highly aware of the costs associated with the transition to renewables, with charges for renewable subsidies now making up about a quarter of the electricity price paid by residential households.

This raises the question: what drives the global shift away from nuclear power despite the substantial economic and environmental costs associated with this policy? We discuss two potential mechanisms. First, the nuclear phase-out may be the result of rational decision-making by risk averse agents.

Specifically, we compare the social costs of the phase-out against the *expected* benefits of this policy. However, nuclear accident risk imposes uncertainty on citizens and the costs associated with nuclear waste disposal are also arguably relatively uncertain. It is thus possible that a sufficiently risk-averse policy-maker could phase-out nuclear to avoid the tail risks associated with nuclear accidents and waste disposal, even though the air pollution costs associated with the phase-out are higher in expectation.

To get a sense of the level of risk aversion required to justify the phase-out, we calculate the probability of a major nuclear accident that would result in the expected benefits from the phase-out being equal to the costs. For this back-of-the-envelope calculation, assume that, absent the phase-out, nuclear plants would have been shut down in the same order but by 2032 instead of 2022. This gives 2032-2011 = 21 years over which the phase-out would reduce nuclear production. Our estimated cost of the phase-out is €3 billion per year; this implies a cumulative cost of the phase-out of €63 billion over 2011-2032. The upper bound estimates of the cost of the Fukushima accident are roughly $750 billion, or €640 billion (JECR, 2019). Assume for simplicity that there can either be no accidents or there can be one Fukushima magnitude accident during this 21 year window. The probability of this Fukushima-scale accident occurring would have to be $0.1 \approx \frac{\text{€63 billion}}{\text{€640 billion}}$ in order for the expected benefits of the phase-out to be equal to the costs of the phase-out. This 1 in 10 chance is far greater than even the most conservative estimates of the probability of an accident of this magnitude occurring in Germany.[9] This in turn suggests that policymakers would have to exhibit an extremely high level of risk aversion in order to rationalize the phase-out based on risk aversion alone.

That being said, citizens may also be anti-nuclear because the risks associated with nuclear power are more salient than the air pollution costs associated with fossil-fuel-fired production. Specifically, the literature on the harmful effects of air pollution is becoming more definitive by the day. However, there is still relatively limited public understanding of the scale of the adverse health consequences of local air pollution exposure. This might be because it is difficult to attribute any single death entirely to pollution exposure from a single power plant. Instead, pollution concentration levels are the result of a wide range of different emitters and air pollution slightly but persistently increases the mortality risk of large exposed populations. Similarly, the costs of climate change will primarily be born by future generations, and linking a future climate event to the carbon emissions from a power plant smokestack is even less straightforward. In contrast, a nuclear accident is a highly visible, yet low probability, event that can be clearly linked back to the offending nuclear

[9] For instance, Wheatley, Sovacool and Sornette (2017) estimates that there is a 50% chance that a Fukushima event (or larger) occurs every 60-150 years across the entire global fleet of nuclear reactors. Germany had less than 4% of the world's nuclear reactors in 2011. Moreover, nuclear reactors in Germany almost certainly come with less accident risk than other parts of the world.

reactor. This may lead both policymakers and the public to over-estimate the ex-ante probability that nuclear accidents will occur as well as costs of these accidents (Slovic, Fischhoff and Lichtenstein, 1979; Slovic, 2010).

Regardless of the underlying causes, it is clear that the German citizenry cares deeply about climate change yet is distinctly anti-nuclear. Policymakers around the world thus face a difficult trade-off. On the one hand, many climate change experts have argued that nuclear power is a necessary part of the shift away from carbon-intensive fossil fuels. Moreover, many voters are willing to incur substantial costs to reduce the risk of climate change. However, many of these same voters are also unwilling to support nuclear power due to fears surrounding nuclear accidents and nuclear waste disposal. Facing this political pressure, countries around the world are shifting away from nuclear production despite the substantial increases in operating costs and air pollution costs associated with this policy. This highlights that it is essential for policymakers and academics to convey the relative costs of climate change and air pollution versus nuclear accident risk and waste disposal to the voting public.

Part II

The Planning Process for Renewable Energy Deployment in the United Kingdom

Chapter 3

Estimating the local impacts of renewable energy projects

3.1 Introduction

Renewable energy projects create a number of local economic impacts. Of primary interest here are the various visual and noise disameneties generally associated with these projects. Credibly estimating the scale of any of these impacts is challenging. Hedonic property value models have become the primary empirical tool for estimating willingness to pay for environmental quality (Bishop et al., 2020). Studies using this approach have shown capitalization into property values of numerous environmental disamenities, such as hazardous waste (Currie et al., 2015), road noise (von Graevenitz, 2018) and water pollution (Keiser and Shapiro, 2018). The primary measure of local impacts utilized here is therefore based on estimating capitalization into property values. In general, the hedonic analysis undertaken here does not seek to differentiate between the various local impacts associated with wind and solar projects, but rather considers them in aggregate through their effects on property values.

To approximate the impacts of a new wind or solar power project on nearby residents and businesses I focus on estimating how the construction of a project is capitalized into local property values and rents. There is a burgeoning literature that uses hedonic methods to estimate the value of various environmental amenities, including those affected by large infrastructure projects (Bishop et al., 2020). One area of focus has been power projects, such as fossil or nuclear power plants (Davis, 2011; Tanaka and Zabel, 2018). Increasingly research has turned to looking at the local impacts of renewable power projects; primarily the visual and noise disamenities caused by wind farms. On balance these studies find negative effects on property values, although the magnitudes can range significantly from finding no effect (Lang, Opaluch and Sfinarolakis, 2014; Hoen and Atkinson-Palombo, 2016), to finding modest or even large reductions (Gibbons, 2015; Sunak and Madlener, 2016; Dröes and Koster, 2016; Jensen et al., 2018; Dröes and Koster, 2020). I find that the median wind project causes a roughly 3-4% reduction in residential property values at distances of around 2km. Effects are larger at closer distances and also increase with the size of a project, although at an attenuating rate. Effects are larger when a property is likely to have direct line-of-sight to the wind farm, and when properties are located in wealthier, less deprived areas. This suggests the bulk of the adverse impact is due to visual intrusion. In reaching these estimates this paper makes a number of important methodological improvements; the most important of which is that I use information on planned but unsuccessful projects to more credibly construct a plausible comparison group and increase confidence in the observed effects.

In addition to looking at wind farms I also provide one of the first estimates of the impact of solar projects on nearby residential property values (Dröes and Koster, 2020). Interestingly, I do not find any statistically significant effects, even at relatively small distances of 1km. This seems consistent with the lower levels of visual intrusion created by solar panels when compared to wind turbines. In addition to looking at solar projects I also expand the scope of my analysis beyond the prior literature and look at impacts on commercial property values. Existing research has focused exclusively on residential property values, with the exception of Haan and Simmler (2018) who look at agricultural land values. The impact on commercial property values is as yet unstudied and seems potentially important if these projects have adverse effects on tourism or displace existing agricultural activity. I do not find statistically significant effects from either wind or solar projects on commercial property values, although these results are less precisely estimated.

The first commercial wind farms in the UK were constructed in the early 1990s. Rapid adoption of wind power took off in the 2000s such that capacity has now grown to 24GW as of 2019, producing 20% of the UK's electricity (BEIS, 2020*a*). This expansion is set to continue, with wind power forecast to provide 40-55% of the UK's electricity by 2030 (NGET, 2019). Projects have tended to be located in the windier and more remote regions of the north and west of the country. Many projects have also been sited in coastal areas with roughly half of the total wind capacity now located offshore. The emergence of solar power in the UK has been more recent with capacity only really starting to grow in 2010 following the adoption of a more generous subsidy regime. By 2019 the UK's solar capacity stood at 13GW and produced 4% of the UK's electricity (BEIS, 2020*a*). Future growth is expected to be modest with solar power forecast to provide 6-7% of the UK's electricity by 2030 (NGET, 2019). Most of this capacity has been located in the flatter agricultural areas in the south of the country where solar potential is highest. Unlike wind power, small-scale residential and commercial solar installations are widespread making up roughly a third of total solar capacity.

Figure 3.1: Renewable Energy Projects in the UK

Notes: These figures show the location of projects and the timing of when they were submitted for planning permission. Project sizes are determined by their capacity (in MW). Projects are classified by their development status. "In Review" are projects that have submitted a planning application but have yet to receive a final decision. "Completed" are projects that have been approved and are either awaiting construction, under construction, operational or have been subsequently decommissioned. "Abandoned" are projects that were refused planning permission or were otherwise withdrawn or halted. The administrative boundaries depicted are the local planning authorities responsible for processing planning applications.

3.2 Empirical Strategy

3.2.1 Property values

Residential property transactions data is from Her Majesty's Land Registry and covers virtually all sales of residential properties in England & Wales since 1995. Each transaction includes a unique identifier for a given property, as well as the date of the sale and the postcode location of the property. Postcodes in the UK are a very granular geographic unit with around 15 households per postcode (approximately equivalent to census blocks in the US). Summary statistics can be found in Table 3.1.

Commercial property rents data is from the Valuation Office Agency (VOA) and provides average annual assessed rental values for commercial properties in England and Wales since 2000. The underlying source of this data is property-level information that VOA collects as part of its role in setting taxes levied on commercial properties, known as business rates. Unfortunately the raw property-level data is not yet available for use in academic research. However, the VOA does still publish detailed data on annual average rents at the Lower Layer Super Output Area (LSOA) level. Fortunately LSOAs are sufficiently granular geographic units (approximately equivalent to census tracts in the US) to ensure there is meaningful variation in exposure to renewable energy projects. Summary statistics can be found in Table 3.2.

3.2.2 Defining treatment

The capitalization analysis throughout this paper consistently uses some variation on a difference-in-differences framework. Treatment is therefore determined by the combination of 1) whether projects are nearby (*distance*), 2) whether projects have come online yet (*post*), and 3) the intensity of exposure as measured by the size of a project (*capacity*).

$$T_{lt} = (distance_{lt} \in k) \cdot post_{lt} \cdot f(capacity_{lt}) \tag{3.1}$$

The proximity of a property to a nearby renewable energy project (*distance*) is determined by whether the distance between that property's location and the centroid of the project falls into a given distance bin, k. For residential properties their location, l, is based on the centroid of their postcode. For commercial properties promixity is taken to be the average of the proximity values for the postcodes within each LSOA. I use five distance bins ($K = 5$). For wind projects these are: 0-2km, 2-4km, 4-6km, 6-8km and 8-10km. This is informed by prior studies which found the primary effects for wind projects are concentrated within distances of less than 3km (Dröes and Koster, 2016;

Table 3.1: Residential Property Transactions Summary Statistics

	Total	Detached	Semi-Detached	Terraced	Flat
Sale price (thousands)	185.1	278.1	165.9	149.3	169.0
	(223.4)	(261.2)	(160.8)	(224.6)	(225.3)
New property	0.0909	0.134	0.0608	0.0563	0.155
	(0.287)	(0.341)	(0.239)	(0.230)	(0.362)
Leasehold tenure	0.222	0.0388	0.0731	0.0924	0.974
	(0.416)	(0.193)	(0.260)	(0.290)	(0.160)
Floor area	90.48	127.9	89.05	82.84	59.70
	(58.06)	(85.30)	(48.95)	(38.97)	(28.01)
Energy efficiency rating	61.32	60.55	60.02	60.30	66.55
	(12.98)	(13.52)	(12.13)	(12.61)	(13.11)
Rural	0.177	0.339	0.175	0.129	0.0645
	(0.381)	(0.473)	(0.380)	(0.336)	(0.246)
Index of Multiple Deprivation	19.48	12.84	18.21	23.96	21.17
	(13.95)	(9.207)	(13.10)	(15.65)	(13.05)
N (millions)	23.90	5.55	6.64	7.34	4.37

Notes: This table shows means and standard deviations are shown for the entire dataset and then for each of four broad housing types. Floor areas and energy efficieny ratings are taken from Energy Performance Certificates and are available for a subset of properties. The rural control is based on whether the output area (OA) that a postcode belongs to was classed as rural in 2011. The Index of Multiple Deprivation is a composite measure of regional living standards where higher numbers refer to more deprived areas. The unit of observation is a sale of a residential property on a given date.

Table 3.2: Commmercial Property Rents Summary Statistics

	Total	Industrial	Retail	Office	Other
Average rental value (thousands)	16.85	19.64	21.60	24.20	9.122
	(29.38)	(37.58)	(48.33)	(49.65)	(13.27)
Average floorspace	303.3	612.8	189.8	240.0	147.6
	(524.7)	(1078.5)	(280.4)	(355.8)	(185.8)
Rental value per m2	61.78	34.93	89.64	89.67	63.43
	(47.17)	(19.14)	(59.70)	(49.76)	(58.80)
Number of properties	64.37	31.34	33.47	34.43	24.54
	(130.4)	(39.46)	(51.70)	(101.3)	(45.58)
Rural	0.217	0.310	0.142	0.199	0.274
	(0.402)	(0.450)	(0.344)	(0.387)	(0.434)
Index of Multiple Deprivation	22.44	23.02	25.35	22.82	22.45
	(15.59)	(15.33)	(16.24)	(15.90)	(15.54)
N (millions)	0.57	0.41	0.33	0.31	0.43

Notes: This table shows means and standard deviations for the entire dataset and then for each of four broad sector categories. The rural control is based on the population-weighted share of output areas (OA) classed as rural in 2011. The Index of Multiple Deprivation is a composite measure of regional living standards where higher numbers refer to more deprived areas. The unit of observation is at the lower layer super output area (LSOA) by year level.

Jensen et al., 2018; Dröes and Koster, 2020) and have completely decayed by around 10km (Gibbons, 2015). For solar projects the distance bins are: 0-1km, 1-2km, 2-3km, 3-4km and 4-5km. The smaller bins are consistent with the likely smaller distance over which these projects are visible.

The temporal specificity of treatment (*post*) is based on the year when a project becomes operational. Though the project data do include exact dates, fully specifying treatment at the postcode-day level is not necessary. This is because there is unlikely to be a sharp change in property values on the date when projects become operational because of the presence of significant anticipation and adjustment effects that persist over several years. This is substantiated by the event study regressions discussed later.

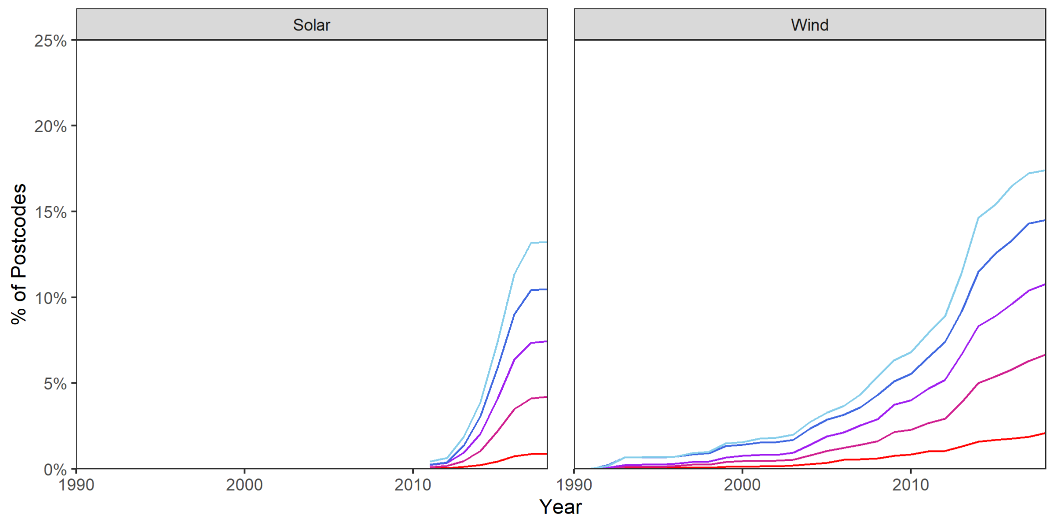
The nature of the treatment effect estimated is then determined by a measure of project size, which I capture as a function of the cumulative wind or solar capacity from all nearby projects (*capacity*). I focus on the cumulative capacity across all projects because this accounts for the fact that many locations have multiple wind or solar projects nearby, and so only focusing on the nearest or the first project will understate the true nature of exposure. Similarly, limiting the analysis to locations that are only near to a single project also risks undermining the external validity of the analysis. I use project capacity as my measure of the intensity of treatment because it is a straightforward measure of the size of a project. Larger capacity solar projects have more solar panels spread across a greater area. Larger capacity wind projects have more wind turbines and/or taller wind turbines. As a robustness check, I also estimate additional specifications using alternative measures of the size of projects (e.g., the number of wind turbines).[1] For reference the results for these alternative measures of project size can be found in the appendix.

Prior studies generally use a simple binary indicator for the presence of any project. In a limited number of cases this is extended by looking at differential effects based on the intensity of exposure (e.g., using different bins for small vs large projects). One of the most recent studies on this topic demonstrates that a log specification does a good job of capturing the general response of the treatment effect to increasing exposure (Jensen et al., 2018). In particular, a log specification captures the attenuation of the treatment effect as project size increases. As we might expect, the first wind turbine or acre of solar

[1]For wind projects an obvious choice is the number of turbines, in line with prior work. This seems particularly important because the relationship between MW of capacity and the number of turbines has been changing over time as turbines become larger. Examining the capitalization effects of both measures can offer valuable insights into whether the move to projects with fewer, larger turbines is mitigating or exacerbating local impacts. For solar projects I considered the land area covered by solar panels to be the most appropriate choice. Unlike wind turbines though, the relationship between solar panel capacity and surface area has remained relatively constant at roughly 5-6 acres per MW (Ong et al., 2013). As such, the results estimated using solar capacity can be simply rescaled where an effect in terms of area covered is desired.

panels should probably have a larger incremental effect than the tenth or the hundreth. I also found a log specification to perform well, and so my preferred functional form is the log of cumulative wind or solar capacity.[2] The resulting treatment effects show how a 1% increase in wind or solar capacity nearby leads to a x% change in property values. For ease of presentation many of the results shown later will convert this into an estimate of the absolute impact for the median project, which is generally around 10MW in size. For reference the results using alternative functional forms (e.g., linear in capacity) can be found in the appendix.

Figure 3.2: Treatment Exposure



Notes: This figure shows the proportion of postcodes over time that are exposed to at least one renewable energy project at a given distance range. The closest distance bin is in red and the furthest is in light blue. Treatment is clearly increasing over time as more projects come online. Treatment begins earlier in the period for wind projects whereas solar projects only began meaningful development after a change in the subsidy regime in 2010. In all regressions I drop any properties at locations that do not fall into one of these distance bins by the end of the analysis period.

3.2.3 Difference-in-difference specification

Throughout this analysis I employ a quasi-experimental difference-in-difference approach. This hinges on comparing changes in property values for locations that have a new renewable energy project constructed nearby to changes in property values for other similar locations that do not have a new renewable energy project constructed nearby. The basic difference-in-difference specification used here is of the general form:

[2]When taking logs of variables that contain zeroes I use the approach set out in (Bellego and Pape, 2019).

$$log(P_{ilrt}) = \sum_{k=1}^{K} \beta_k T_{lt} + \gamma X_{it} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{3.2}$$

Here P is a measure of the value of a property (or group of properties), i, at location, l, within region, r, in year, t. For the residential property sales this is the transaction price of a property and for the commercial property rents this is the annual average rental value per square meter. Unless otherwise specified the treatment effect coefficients, β_k, capture the % change in property values from a 1% increase in wind or solar capacity in distance bin k. Regressions are estimated separately for wind and solar projects and jointly for all k distance bins. In addition to estimating the regressions jointly for all k distance bins, I also repeat the analysis in a sequential manner for a set of distance circles. In this case separate regressions are estimated with treatment determined by distances of 0-2km, 0-4km, 0-6km, 0-8km and 0-10km for wind projects, and 0-1km, 0-2km, 0-3km, 0-4km and 0-5km for solar projects. This alternative approach helps make comparisons to other studies, as well as facilitating the examination of possible sources of heterogeneity (discussed later).[3] Standard errors are clustered based on location to account for correlation between nearby observations.[4]

In all regressions I limit the sample to properties in locations that ever fall into one of the included distance bins. For the joint regressions this means the analysis is limited to locations within 10km of a wind or 5km of a solar project by the end of the period.[5] Properties are treated in a given time period when a project is completed nearby (i.e. within a relevant nearby distance bin). The resulting control group is formed by properties that do not experience a change in their treatment status during that period. This includes locations that have yet to have a project completed and locations where a project was already completed in previous time periods. This ensures that the control observations are broadly comparable to those undergoing treatment.[6]

[3]The primary benefit here is computational. For the regressions with all k distance bins estimated jointly, the memory requirements when estimating these in an event study setup with multiple interactions for heterogeneous treatment effects quickly becomes prohibitive. The distance circles approach that estimates treatment effects based on one distance at a time mitigates this somewhat, whilst still producing coefficients that are broadly similar.

[4]For the residential property regressions I cluster at the output area (OA) level and for the commercial property regressions I cluster at the middle layer super output area (MSOA) level

[5]For solar projects this is 34% of the residential sales sample and 32% of the commercial rents sample. For wind projects this is 34% of the residential sales sample and 30% of the commercial rents sample.

[6]To further ensure the focus is on the rural and suburban areas where these visual and noise disamenities are likely to be most relevant I also dropped any remaining properties located in the core of major urban areas. In most cases these locations had already been dropped due to wind and solar projects not being sited in built up areas. However, there were a small number of exceptions where a few small wind or solar projects were sited in

I account for unobservable time-invariant determinants of property values using a rich set of location fixed effects, λ_l. For the residential property regressions these are at the postcode-by-housing-type level. Properties in a given postcode of a given housing type are likely to be highly comparable, particularly because postcodes only include around fifteen properties each.[7] To explore purely within-property variation I also estimate versions with address-level unit fixed effects.[8] For the commercial property regressions the data are already aggregated to regional annual totals by LSOA. As such the location fixed effects are at the LSOA level. This presents a challenge in that any LSOA may have a range of different commercial activities contributing to the average. However, this is mitigated somewhat by estimating these regressions both for the average of all commercial properties, and for four sectors within each LSOA: retail, office, industrial and other. Moreover, whilst an LSOA is a more aggregated unit than a postcode it is still relatively small, corresponding to roughly one thousand households. As such, commercial activities within a given LSOA are still likely to be relatively homogenous, particularly at the sector level.

To account for unobservable time-variant determinants of property values all regressions include time fixed effects, θ_{rt}, at the year-of-sample-by-region level. I also explore the sensitivity of my results to using more granular regions to increase the richness of these fixed effects.[9] Of course, allowing the time fixed effects to vary by region does risk absorbing a portion of the treatment effect of interest and so this should be kept in mind when interpreting the results.[10]

industrial areas (e.g., along the River Thames in London). Dropping these manually ensured the analysis was not unduly influenced by the very large number of observations in these dense urban areas.

[7]As can be seen in Table 3.1 there are clearly substantial differences between property types and so controlling for these is important. Where this isn't the case though, a postcode fixed effect can be averaging across very different property types. Increasing the granularity of the fixed effects to the postcode-by-housing-type level resolves this in a far more robust manner than including a simple aggregate control for housing type.

[8]This has the benefit of capturing property-specific factors that can't be captured by the post code fixed effect. The drawback here is that the estimation can only use the subset of addresses with multiple sales, which reduces statistical power and raises the issue that these repeatedly sold properties are not representative of properties more generally.

[9]First I use the eleven regions that were formerly known as Government Office Regions. These comprise nine English regions and then Wales and Scotland and range in size from roughly 1 to 4 million households so are fairly analogous to small US states. Second I use the roughly four hundred local authorities in the UK which are more analoguous to US counties.

[10]I did explore just using a single set of year-of-sample effects for the whole of the UK. However, different parts of the UK have clearly experienced differential rates of economic growth and property value appreciation over this period, and these divergences are probably at least partially correlated with treatment. For instance, the more prosperous south is also where the majority of solar projects are located, whilst the north where economic growth has lagged behind has also seen a larger portion of wind projects.

Finally, to capture observable time-variant determinants of property values a limited set of additional controls, X, are included. For residential properties the available controls include whether a sale is for a new home and the type of tenure (e.g., freehold vs leasehold).[11] For a subset of the residential properties there is also information on house floor areas and energy efficiency ratings. For commercial properties the available controls include average floor areas.

Identification of a credible causal effect using a difference-in-difference approach faces a number of challenges in this context. Key to this is the parallel trends assumption; namely that in the absence of treatment the treated and control locations would have experienced similar changes in property values. If the location and timing of wind and solar projects was randomly assigned we could be confident that this assumption holds. However, here the treatment is obviously not randomly assigned. Instead there is selection of locations into treatment in terms of where projects are actually approved and built. Moreover, conditional on ever being treated there is also selection in terms of when treatment happens (earlier vs more recent projects). Some of the major factors driving selection into treatment may be seemingly unrelated to residential or commercial property values (e.g., wind speed). However, other factors almost certainly are related to selection into treatment during the planning process and directly or indirectly related to local property values (e.g., visual or historical appeal of local landscape, local political preferences, presence of important ecological habitats and wildlife). The primary solutions to this challenge that I have set out thus far are the decision to a) limit the controls to locations that are near to a completed project by the end of the period, and b) make the parallel trends assumption conditional on a rich set of fixed effects and controls. This ensures that the control properties forming the counterfactual are very similar to treated properties and that the variation being used for identification is not confounded by other factors.

I augment the difference-in-difference setup using a series of event studies. Here the treatment variable is now interacted with a series of event dummies indicating whether a given observation is s years before (pre) or after (post) the date when a project became operational. I include ten years of pre-periods ($S_{pre} = -10$) and five years of post-periods ($S_{post} = 5$), the last of which also captures any observations that are more than five years after a project becomes operational. This should allow for sufficient time for the any effects to materialize. The resulting specification is of the form:

$$log(P_{ilrt}) = \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta_{k,s} T_{lt} + \gamma X_{ilt} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{3.3}$$

[11] Someone with a freehold property owns the property and the land it stands on. A leaseholder owns the property but not the land is built on. The latter is more commonly used for flats and apartments where the property owner is only purchasing a part of an entire building.

The event study approach has a number of benefits in this setting which is why it is my preferred specification. First, it helps identify potential anticipation and adjustment effects. Because planning and construction can last several years we might expect anticipatory effects well before a project becomes operational. It also seems plausible that it could take time for the housing market to adjust before the true scale of the local effects from a new project become clear. Both of these factors mean that the standard difference-in-difference treatment coefficients estimated using Equation 3.2 may underestimate or overestimate the true effect. Properly accounting for these anticipation and adjustment effects is therefore important for understanding the true capitalization effect and the manner in which it manifests. Second, the event study can help provide some supporting evidence that parallel trends hold in the pre-period. Third, a number of recent papers have shown that difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018). One partial solution is to employ some form of event study as it can more consistently pin down the source of identifying variation and how it is affected by variation in treatment timing (Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019). Of course, the main drawback to the event study approach is that it requires estimating a far larger number of coefficients which reduces statistical power.

3.2.4 Comparing approved and refused projects

At present the analysis follows prior studies by using locations near completed projects to define both the treated and control groups. However, it seems reasonable to think that locations near to completed projects are not the only areas with properties that could act as plausible controls. For example, there are many remote windy areas in the UK that have properties that are comparable to treated ones, but that have not yet themselves had a wind farm completed nearby. I take advantage of the unique information available in the UK's renewable energy planning database to construct an alternative comparison group based on properties near to proposed projects that ultimately were not built.

To do this, I first construct a full secondary set of treatment variables in the exact same manner set out previously, but this time derived from projects that were proposed but ultimately failed. For failed projects treatment happens based on the date when a project would have become operational if it had been approved and completed.[12] These additional treatment variables for the failed projects, T^F, are included in the regression alongside the original treatment variables for the completed projects, T^C. This can be seen in the modified version of Equation 3.2 below, and the intution is the same for modifying

[12] Note that this is based on the final planning decision and so is after accounting for any delays created by the appeal process.

Equation 3.3.

$$log(P_{ilrt}) = \sum_{k=1}^{K} \beta_k^C T_{lt}^C + \sum_{k=1}^{K} \beta_k^F T_{lt}^F + \gamma X_{ilt} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{3.4}$$

Coefficients are estimated as before but now a direct comparison can be made between the coefficents for the completed projects and the coefficients for the failed projects. This change has a number of possible benefits. First, the sample size of properties available for use in the estimation is larger which improves statistical power. This is because I still include any properties at locations that ever fall into one of the included distances bins, but the distance bins now refer to both completed and failed projects. Second, the control groups for each distance bin are now more targeted because I can more explicitly compare areas that were or could have been a certain distance from a project. Third, there is the possibility of looking more explicitly at sorting behavior. However, this expansion of the control group has some clear drawbacks, not least the fact that comparing locations with completed projects to those with failed projects puts concerns about selection bias into even sharper relief.

To tackle possible concerns about selection, I exploit information about the planning processes for projects. I repeat the estimation for all specifications set out thus far but now interact treatment with whether a project was subject to an appeal. This offers a potential way to mitigate concerns about selection bias by focusing on the effects for a subset of more "marginal" projects (i.e. projects that only just got built or only just failed). Marginal completed projects are those where the appeal overturns the initial refusal and marginal failed projects are those where the appeal upholds the initial refusal. Limiting the analysis to properties treated by this subset of projects rules out locations with projects that a) were almost certain to be approved and likely imposed smaller local disamenities, and b) were almost certain to be refused and likely imposed larger local disamenities. The remaining projects were clearly thought to be sufficiently undesirable by the local planning authority to warrant refusal and thought to be sufficiently valuable by the developer to warrant appealing. As such it seems plausible that this subset of projects is more credibly comparable than simply using the entire sample of projects.

3.2.5 Differential impacts by visibility

The visual impact of wind and solar projects is consistently cited as a key reason that projects are refused planning permission. Prior work has also found that negative impacts on local property values are primarily due to visual disamenity (Gibbons, 2015; Sunak and Madlener, 2016). I examine whether properties that are likely to have direct line-of-sight to a project experience different effects than properties where projects are obscured by the landscape (e.g., behind a hill).

To isolate the visual impacts of wind and solar projects I conduct a geospatial analysis to determine whether properties are likely to have direct line-of-sight to a project. An illustration of this analysis can be seen in Figure 3.3. This figure shows a map of the area surrounding the Caton Moor Wind Farm, denoted by the red diamond in the center. The top panel shows the surrounding 6km and the bottom panel shows the surrounding 12km. The black/grey/white points denote the postcodes where properties are located. Postcodes in black have no direct line-of-sight to the project. Postcodes in white have full direct line-of-sight to the project. Postcodes in grey have some partial line-of-sight (e.g. the tip of the turbine blades might be visible, whilst much of the base of the turbine is obscured).

This visibility metric was calculated using the GB SRTM Digital Elevation Model compiled by Pope (2017). Project coordinates were taken from the Renewable Energy Planning Database. In the limited number of cases where the coordinate was missing, or appeared erroneous, the postcode centroid from the address listed in the planning database was used. Postcode coordinates were taken from the ONS postcode lookup file. All spatial data was converted to the Ordanance Survey National Grid reference system.

In addition to specifying coordinates in the east-west and north-south directions, determine line-of-sight also requires specifying an elevation for each point. The default is to simply use the ground-level elevation from the digital elevation model. No person standing by their property is realistically looking out at ground level, and so I assumed that the coordinate for each post code should be set at head height, around 1.5m off the ground.

For the wind and solar projects what matters is the visibility of the structures being installed (i.e., wind turbines or solar panels). For solar projects this is relatively trivial because panels are very homogenous and usually installed in very similar ways. As such I assume that the top of the solar panels are located at 3m off the ground. For wind projects the height of the turbines is far more heterogenous, particularly as turbines have increased substantially in size over time. The planning dataset also does not include information on wind turbine tip heights. Fortunately it is possible to calculate the average capacity of the turbines installed by dividing the total capacity by the number of turbines. Turbine capacity has a fairly stable relationship to turbine size. I use data on thousands of different turbine models in The Wind Power Turbine Database (Pierrot, 2019) to fit a simple regression model that traces out the effectively quadratic relationship between turbine capacity and turbine height. I then apply this to the information on turbine capacity in the project database. The resulting turbine tip heights range from around 50m to in excess of 200m. This is the height off the ground that I use for the project locations.

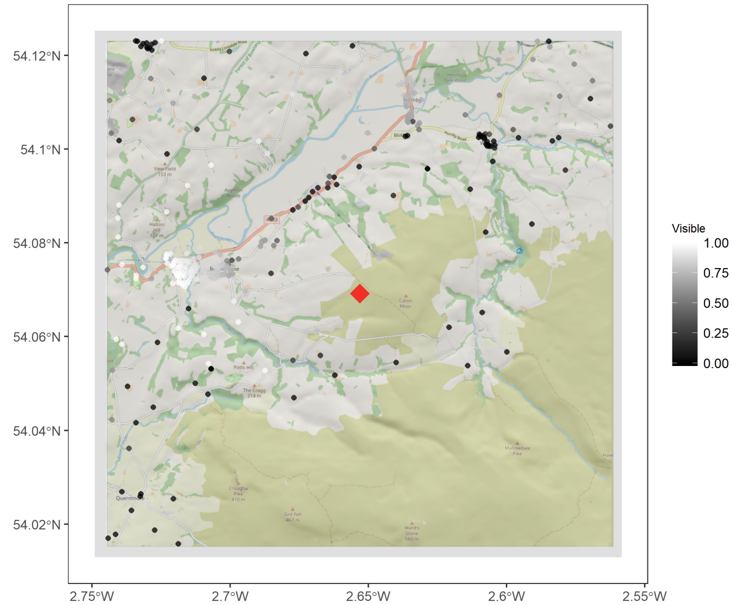
Finally, I conduct a direct line-of-sight analysis using the digital elevation model and each project-postcode pair within a 20km radius. For this I use the intervisibility algorithm developed by Cuckovic (2016) in QGIS. As well as calculating a binary indicator of whether there is direct line-of-sight between two points, it is also possible to use this algorithm to calculate what portion of the target structure is visible. So, if the top 40m of a 100m wind turbine is visible then I calculate a visibility metric of 0.4. Ultimately I convert this to a binary indicator which takes the value one if any of the project is visible. The results do not appear particularly sensitive to the use of alternative cutoffs. I did consider looking at the impact of partial visibility, but this is likely not possible for this particular dataset given the measurement error in the coordinate locations and the lack of information on the area covered by each project.

It is worth noting that this approach is certainly not without its flaws. For instance, it only uses the central point of a project rather than the area covered, and it can't account for other features that may act to block line-of-sight such as trees or buildings. Nevertheless, it should still be sufficient to isolate clear differences in visibility.

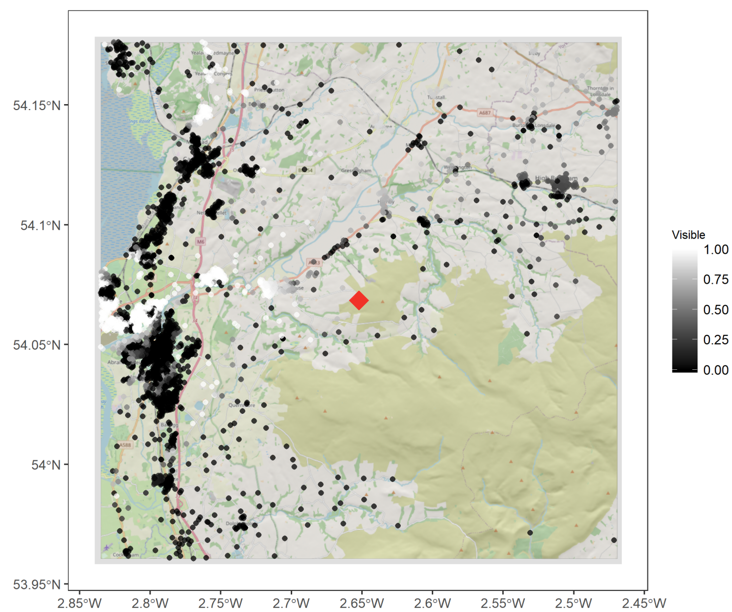
3.2.6 Differential impacts by deprivation

The second key source of differential impacts that I study is whether effects are different in wealthy neigborhoods relative to poorer neighborhoods. In general we might expect the impact of a nearby wind or solar project on property values to be larger in both absolute and proportional terms for properties in wealthier neighborhoods. This is because wealthier neighborhoods will tend to already enjoy greater value from the kinds of environmental amenities that a new renewable energy project would adversely impact, like unspoiled green space, historic landscapes and beautiful views (Gibbons, Mourato and Resende, 2014). Properties located in more deprived areas, on the other hand, are already more likely to be characterized by unsightly and noisy industrial development. To explore this possible distinction I examine whether properties that are in more deprived areas experience different effects than properties in less deprived areas. To do this I use the UK's Index of Multiple Deprivation. This measure classifies neighborhoods based on their relative level of deprivation by weighting across a range of indicators covering income, employment, education, health, crime, housing quality and environmental quality. I define more deprived areas as those above the median on the index, and less deprived areas as those below the median.

Figure 3.3: Illustration of Postcode to Project Visibility



(a) 6km radius



(b) 12km radius

Notes: This figures shows the visibility of a wind project from different postcodes. The red diamond is the Caton Moor Wind Farm. The black and white points are postcodes. Black points do not have direct line-of-sight. White points do have direct line-of-sight.

3.3 Results

The capitalization results are primarily summarized by the event study plots. Further detailed tables can be found in the appendix.

3.3.1 Impacts on residential property values

Wind projects

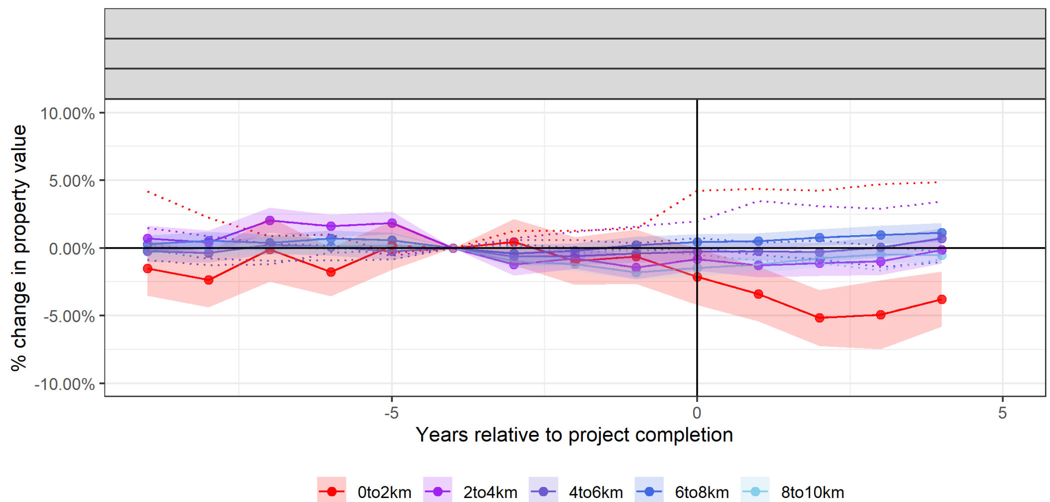
For wind projects the event study in Figure 3.4 shows a reduction in property values of around 3-4% for properties located within 2km of a newly built 10MW project. This effect is minimal at distances of 2-4km and decays to virtually zero beyond 4km. The log specification also means the effect attenuates as the size of a project increases, with the first wind turbine being the most costly. The effects observed here are of a similar magnitude to those found in previous studies. The event study plots make clear the presence of important anticipation effects one to two years before projects ultimately come online, as well as adjustment effects over the following two years. This is consistent with the planning and construction process for wind projects generally taking around two to three years.

In a novel addition to the existing literature, I am also able to check the observed effects for the treated locations where projects were built against the changes in the control locations where projects failed. The dotted lines in Figure 3.4 indicate that in locations where projects were proposed but ultimately failed there is no significant negative impacts on property values. If anything those locations see an appreciation in property values once the fate of the proposed project becomes clear. This may be in part due to sorting behavior and the increasing value placed on any remaining locations yet to be "spoiled" by the construction of a wind farm.

The event study results provide strong supportive evidence that prior to any anticipation in the pre-period there are parallel trends for both completed and failed projects. This validation of the difference-in-difference empirical strategy has been lacking in prior studies on this particular topic, in large part due to studies relying on smaller datasets or failing to examine pre- and post-treatment trends over a long time period.

Table 3.3 illustrates how these effect sizes vary across a range of specifications. Columns 1 to 3 are results from a standard difference-in-difference estimation. Columns 4 to 6 are results from the equivalent event studies, with the treatment effects calculated as the difference between the earliest five pre-period coefficients and the five post-period coefficients. It is immediately clear that the treatment effects using the event study approach are larger. This is likely due to the event study better capturing anticipation and adjustment

Figure 3.4: Residential Property Values Event Study Results for Wind Projects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

effects, as well as mitigating potential biases due to the staggered nature of treatment in this setting. The other source of variation across columns is the choice of location fixed effects. The effects are stable across specifications, even when limiting the data to repeat sales properties and using address-level fixed effects.

Table 3.3: Residential Capitalization for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)
Completed						
0to2km	-2.38^{***}	-2.01^{***}	-1.76	-3.28^{***}	-2.77^{***}	-3.37^{***}
	(0.55)	(0.49)	(0.78)	(0.64)	(0.65)	(0.87)
2to4km	0.26	-0.22	0.04	-1.97^{***}	-2.20^{***}	-1.69^{***}
	(0.29)	(0.24)	(0.32)	(0.33)	(0.30)	(0.37)
4to6km	0.86^{***}	0.41	0.03	0.04	0.09	0.30
	(0.21)	(0.19)	(0.25)	(0.22)	(0.21)	(0.26)
6to8km	0.62^{**}	0.33	1.05^{***}	0.25	0.27	0.37
	(0.20)	(0.17)	(0.24)	(0.20)	(0.18)	(0.24)
8to10km	-0.47^{*}	-0.74^{***}	-0.50^{*}	-0.84^{***}	-0.93^{***}	-0.56^{*}
	(0.18)	(0.16)	(0.21)	(0.19)	(0.17)	(0.21)
Failed						
0to2km	2.52^{***}	3.07^{***}	3.51^{***}	2.22^{***}	2.89^{***}	2.64^{***}
	(0.53)	(0.50)	(0.63)	(0.56)	(0.55)	(0.68)
2to4km	2.80^{***}	2.29^{***}	1.52^{***}	2.57^{***}	2.51^{***}	1.71^{***}
	(0.30)	(0.26)	(0.35)	(0.32)	(0.29)	(0.35)
4to6km	0.09	0.04	-0.10	0.86^{***}	1.10^{***}	0.75^{**}
	(0.21)	(0.19)	(0.26)	(0.23)	(0.21)	(0.26)
6to8km	-0.29	-0.50^{**}	-0.59^{*}	-0.16	-0.03	0.14
	(0.19)	(0.17)	(0.24)	(0.20)	(0.18)	(0.24)
8to10km	-0.84^{***}	-1.10^{***}	-0.81^{***}	-0.92^{***}	-1.01^{***}	-0.87^{***}
	(0.17)	(0.15)	(0.20)	(0.18)	(0.16)	(0.20)
R-Squared	0.96	0.90	0.82	0.96	0.90	0.82
N (millions)	5.71	8.07	8.21	5.71	8.07	8.21
Log Functional Form	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	Y	Y	Y
Address Fixed Effects	Y	–	–	Y	–	–
Postcode Fixed Effects	–	Y	–	–	Y	–
LSOA Fixed Effects	–	–	Y	–	–	Y
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

One concern with the distance bins approach is that the time fixed effects will be overwhelmingly determined by properties in the outermost distance bins as these have the most observations. To check that this is not driving the results I also estimate five separate regressions for a series of expanding distance circles. In Table 3.4 each column is based on a different distance circle, with an increasing number of observations as the circle gets larger. The effects using this approach are broadly comparable to those using distance bins. Beyond this I also conduct a number of robustness checks of the analysis using alternative fixed effects and by comparing the event study approach to the findings from directly estimating a single coefficient. All of these results can be found in the appendix.

Table 3.4: Residential Capitalization for Wind Projects by Distance Circles

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, ,	-3.27^{***}	-3.06^{***}	-1.25^{***}	-0.56^{***}	-0.57^{***}
	(0.64)	(0.27)	(0.16)	(0.12)	(0.10)
Failed					
, ,	3.29^{***}	2.70^{***}	1.79^{***}	1.00^{***}	0.41^{***}
	(0.55)	(0.26)	(0.16)	(0.12)	(0.10)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

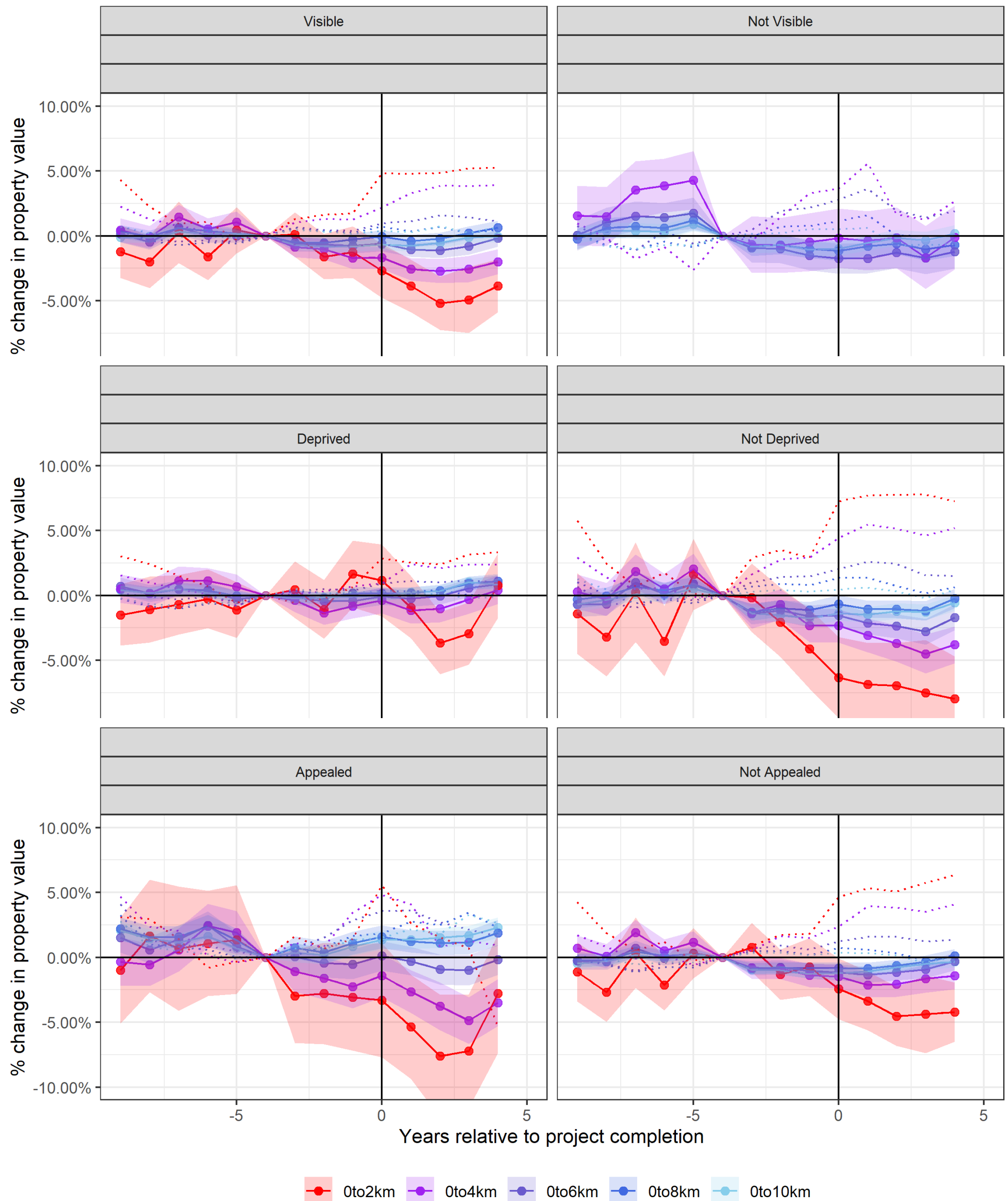
Lastly, I look at differential effects. These results can be seen in Figure 3.5. Note that these results also use the approach of estimating five separate regressions for a series of expanding distance circles. As expected, I find that the property value impacts of wind projects appear to be more pronounced in locations near a project that was appealed, for properties that have direct line-of-sight to a project, and for properties in less deprived areas.

Lastly, Table 3.5 shows the results of the differential effects analysis. Note that these results also use the approach of estimating five separate regressions for a series of expanding distance circles.

The main approach taken in the capitalization analysis measures wind project size as being a function of the capacity of a project in MW. However, there are other ways to capture the relative size of a project, such as the land area covered by the solar panels, or the number of wind turbines. In the case of solar projects, the relationship between total capacity and the land area covered has been broadly stable. For wind projects though, the relationship between total capacity and the number of turbines has been changing as turbines have gotten larger.

To explore the possible implications of this for the findings on wind projects, I re-run the capitalization analysis with number of turbines as the measure of project size, rather than total capacity. Table 3.6 shows that the results are largely unchanged. In fact the coefficient sizes are broadly similar because the average size of wind turbines over this period has tended to be on the order of around 1MW.

Figure 3.5: Residential Capitalization Event Study for Wind Projects with Differential Effects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

Table 3.5: Residential Capitalization for Wind Projects with Differential Effects

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
Not Appealed, Not Visible, Deprived		−2.09	−1.00	0.01	0.14
		(1.03)	(0.50)	(0.33)	(0.23)
Not Appealed, Not Visible, Not Deprived		−2.59*	−1.62*	−1.04*	−0.27
		(0.95)	(0.58)	(0.41)	(0.33)
Not Appealed, Visible, Deprived	−0.25	−2.04***	−0.75**	−0.16	0.05
	(0.85)	(0.38)	(0.25)	(0.20)	(0.16)
Not Appealed, Visible, Not Deprived	−5.04***	−2.93***	−0.19	−0.17	−1.39***
	(1.04)	(0.53)	(0.35)	(0.27)	(0.22)
Appealed, Not Visible, Deprived		6.66*	4.62***	3.45***	2.04***
		(2.60)	(1.22)	(0.73)	(0.54)
Appealed, Not Visible, Not Deprived		−2.48	−7.88***	−4.68***	−3.18***
		(2.67)	(1.74)	(1.04)	(0.75)
Appealed, Visible, Deprived	−0.45	−0.30	1.01**	1.01***	1.03***
	(1.55)	(0.65)	(0.35)	(0.28)	(0.24)
Appealed, Visible, Not Deprived	−8.05***	−7.72***	−6.67***	−3.24***	−0.53
	(2.12)	(1.20)	(0.82)	(0.65)	(0.50)
Failed					
Not Appealed, Not Visible, Deprived		4.15***	2.43***	1.92***	1.13***
		(0.86)	(0.45)	(0.30)	(0.21)
Not Appealed, Not Visible, Not Deprived		1.76	2.39***	0.91*	0.13
		(0.92)	(0.59)	(0.38)	(0.31)
Not Appealed, Visible, Deprived	2.26***	2.09***	1.17***	0.90***	0.57***
	(0.61)	(0.33)	(0.23)	(0.18)	(0.14)
Not Appealed, Visible, Not Deprived	5.78***	4.09***	2.46***	1.02***	0.09
	(1.01)	(0.48)	(0.30)	(0.26)	(0.21)
Appealed, Not Visible, Deprived		−2.81	0.16	−1.79	−0.47
		(2.39)	(1.24)	(0.86)	(0.64)
Appealed, Not Visible, Not Deprived		12.52***	3.14*	0.32	−1.84*
		(2.52)	(1.26)	(0.92)	(0.77)
Appealed, Visible, Deprived	−3.78	−5.32***	−3.06***	−2.34***	−0.60
	(2.04)	(1.20)	(0.79)	(0.59)	(0.45)
Appealed, Visible, Not Deprived	3.46	0.76	0.49	2.97**	2.94***
	(4.30)	(1.46)	(0.97)	(0.91)	(0.77)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Table 3.6: Residential Property Values Results for Wind Projects with Number of Turbines

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
	-3.40^{***}	-2.43^{***}	-0.65^{**}	-0.20	-0.46^{***}
	(0.72)	(0.31)	(0.18)	(0.14)	(0.11)
Failed					
	3.86^{***}	3.64^{***}	2.61^{***}	1.52^{***}	0.81^{***}
	(0.68)	(0.31)	(0.19)	(0.15)	(0.12)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Solar projects

For solar projects I find no consistent evidence of an impact on residential property values. Figure 3.6 makes clear there is no noticeable change in property values when a solar project is built nearby. This is the case even though the distance bins being used are smaller, with the smallest capturing properties that are within 1km of a project. There is also no appreciation effect for properties near failed projects either.

Table 3.7 largely confirms the findings in the event study plot, with again no consistent effect emerging across a range of specifications.

Table 3.8 shows the results of the analysis using the alternative distance circles approach for solar projects. As with the wind projects the same broad correspondence with the distance bins approach is still apparent. Lastly, I check the robustness of my findings using a range of alternative specifications, all of which can be found in the appendix.

Figure 3.7 shows the results of the analysis of differential effects for solar projects. Here again there is no consistent evidence of a statistically significant effect, even for the properties with direct line-of-sight to appealed projects.

Table 3.9 and shows the results of the analysis of differential effects for solar projects. Here again there is no consistent evidence of a statistically significant effect, even for the properties with direct line-of-sight to appealed projects.

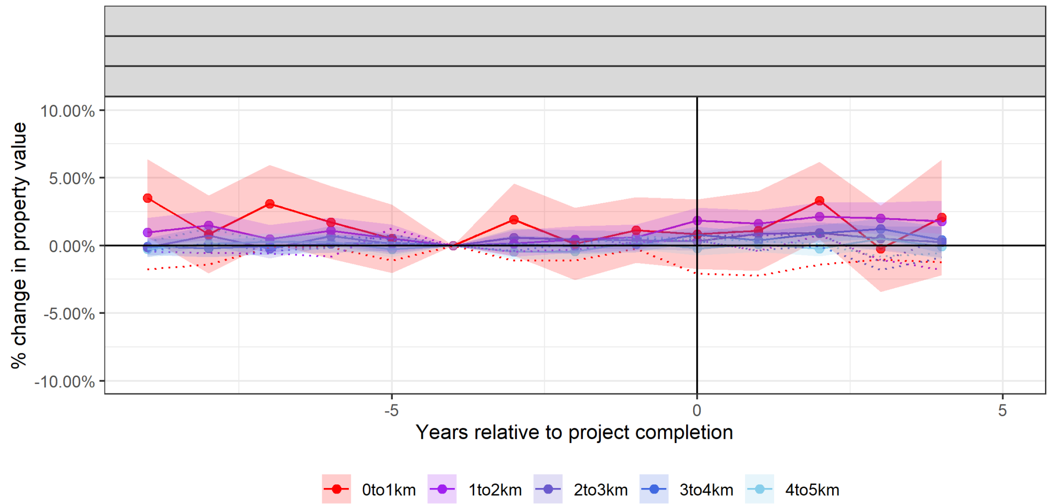
Table 3.7: Residential Capitalization for Solar Projects

	(1)	(2)	(3)	(4)	(5)	(6)
Completed						
0to1km	-0.17	0.46	-0.54	-1.31	-0.51	-1.49
	(0.69)	(0.72)	(1.43)	(0.77)	(0.86)	(1.45)
1to2km	1.26^{***}	1.33^{***}	1.21^{*}	1.08^{**}	0.98^{**}	0.96
	(0.34)	(0.30)	(0.48)	(0.35)	(0.32)	(0.47)
2to3km	0.46	0.56^{*}	0.55	0.19	0.34	0.31
	(0.28)	(0.24)	(0.32)	(0.29)	(0.25)	(0.33)
3to4km	0.84^{***}	0.98^{***}	0.73	0.57^{*}	0.73^{***}	0.66
	(0.21)	(0.19)	(0.32)	(0.23)	(0.21)	(0.33)
4to5km	-0.09	0.15	-0.04	-0.34	0.00	-0.32
	(0.20)	(0.17)	(0.26)	(0.21)	(0.19)	(0.26)
Failed						
0to1km	-0.96	-1.63	-0.12	0.10	-0.70	0.20
	(1.10)	(1.07)	(1.28)	(1.33)	(1.37)	(1.56)
1to2km	-0.02	-0.14	-0.30	0.30	-0.18	0.07
	(0.43)	(0.37)	(0.58)	(0.50)	(0.46)	(0.60)
2to3km	-0.62	0.05	0.73	0.03	0.32	0.54
	(0.39)	(0.31)	(0.43)	(0.48)	(0.39)	(0.51)
3to4km	-0.70^{*}	-0.19	0.04	-1.08^{**}	-0.67	-1.05
	(0.27)	(0.24)	(0.45)	(0.34)	(0.31)	(0.71)
4to5km	-0.21	-0.16	-0.17	-0.28	-0.51	-0.38
	(0.26)	(0.22)	(0.37)	(0.32)	(0.28)	(0.44)
R-Squared	0.96	0.91	0.83	0.96	0.91	0.83
N (millions)	5.82	8.18	8.31	5.82	8.18	8.31
Log Functional Form	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	Y	Y	Y
Address Fixed Effects	Y	–	–	Y	–	–
Postcode Fixed Effects	–	Y	–	–	Y	–
LSOA Fixed Effects	–	–	Y	–	–	Y
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Figure 3.6: Residential Capitalization Event Study for Solar Projects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

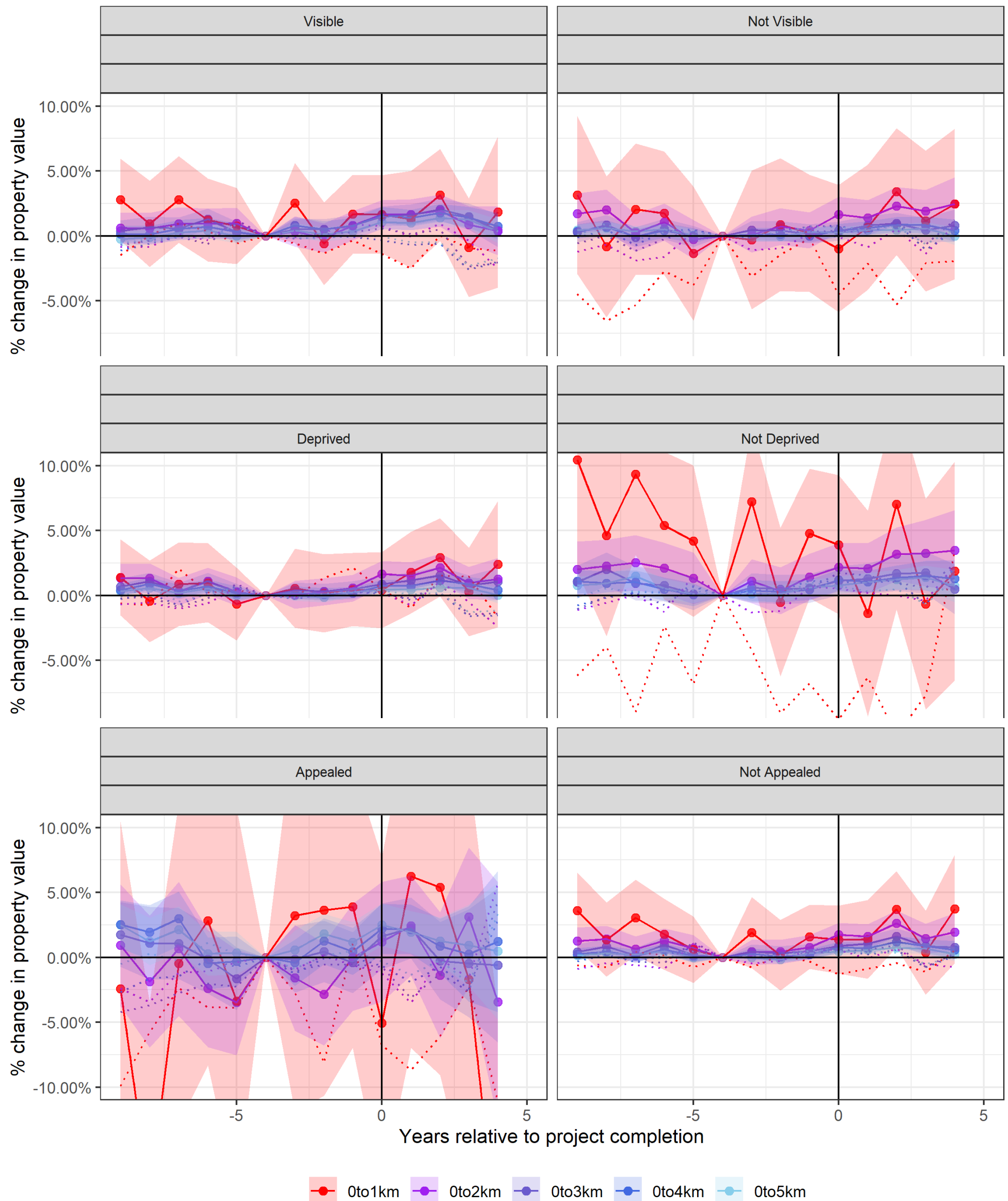
Table 3.8: Residential Capitalization for Solar Projects by Distance Circles

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, ,	-0.02	0.82^{*}	0.57^{**}	0.55^{***}	0.32^{**}
	(0.85)	(0.30)	(0.20)	(0.14)	(0.11)
Failed					
, ,	-0.26	0.39	0.40	-0.08	-0.25
	(1.37)	(0.45)	(0.30)	(0.22)	(0.17)
R-Squared	0.91	0.91	0.91	0.91	0.91
N (millions)	0.33	1.83	3.93	6.13	8.18

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Figure 3.7: Residential Capitalization Event Study for Solar Projects with Differential Effects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

Table 3.9: Residential Capitalization for Solar Projects with Differential Effects

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
Not Appealed, Not Visible, Deprived	1.25	0.99	0.21	0.08	-0.22
	(1.24)	(0.50)	(0.33)	(0.21)	(0.16)
Not Appealed, Not Visible, Not Deprived	-2.51	0.43	-0.01	0.38	-0.08
	(3.06)	(1.07)	(0.57)	(0.39)	(0.31)
Not Appealed, Visible, Deprived	1.19	0.25	0.30	0.51	0.62^{**}
	(1.09)	(0.41)	(0.29)	(0.24)	(0.19)
Not Appealed, Visible, Not Deprived	-6.42	0.44	1.20	1.39^{**}	0.91^{*}
	(2.95)	(0.86)	(0.56)	(0.43)	(0.36)
Appealed, Not Visible, Deprived	3.63	1.93	-1.20	0.46	0.67
	(8.14)	(2.12)	(1.54)	(1.26)	(1.06)
Appealed, Not Visible, Not Deprived	-29.76	5.80	3.85	1.91	0.38
	(67.70)	(5.15)	(4.31)	(3.50)	(2.65)
Appealed, Visible, Deprived	-53.11^{***}	2.68	1.18	-0.13	0.49
	(6.23)	(2.61)	(1.46)	(1.33)	(1.44)
Appealed, Visible, Not Deprived	-130.90	3.93	2.77	1.37	-1.48
	(67.99)	(2.98)	(2.02)	(1.94)	(1.69)
Failed					
Not Appealed, Not Visible, Deprived	0.61	0.42	-0.09	-0.19	-0.06
	(2.59)	(0.88)	(0.46)	(0.32)	(0.27)
Not Appealed, Not Visible, Not Deprived	8.76	1.37	2.77^{***}	1.73^{**}	1.47^{**}
	(4.81)	(1.10)	(0.74)	(0.53)	(0.43)
Not Appealed, Visible, Deprived	-1.25	-0.89	-1.18	-1.25^{*}	-1.02^{*}
	(2.03)	(0.75)	(0.61)	(0.47)	(0.36)
Not Appealed, Visible, Not Deprived	-2.57	1.20	-0.01	-0.63	-0.89
	(5.65)	(1.29)	(0.90)	(0.70)	(0.55)
Appealed, Not Visible, Deprived	-4.83	3.15	1.58	0.06	-0.15
	(7.38)	(2.34)	(1.44)	(0.95)	(0.77)
Appealed, Not Visible, Not Deprived	9.27	-4.80	3.32	4.85^{*}	0.91
	(6.18)	(6.67)	(2.63)	(1.74)	(1.17)
Appealed, Visible, Deprived	5.36	4.03	4.05	1.17	0.52
	(4.57)	(3.16)	(2.09)	(1.60)	(1.39)
Appealed, Visible, Not Deprived	-55.72^{***}	-7.55	-6.00	-7.56	-5.28
	(13.94)	(3.46)	(2.92)	(3.42)	(2.93)
R-Squared	0.91	0.91	0.91	0.91	0.91
N (millions)	0.33	1.83	3.93	6.13	8.18

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

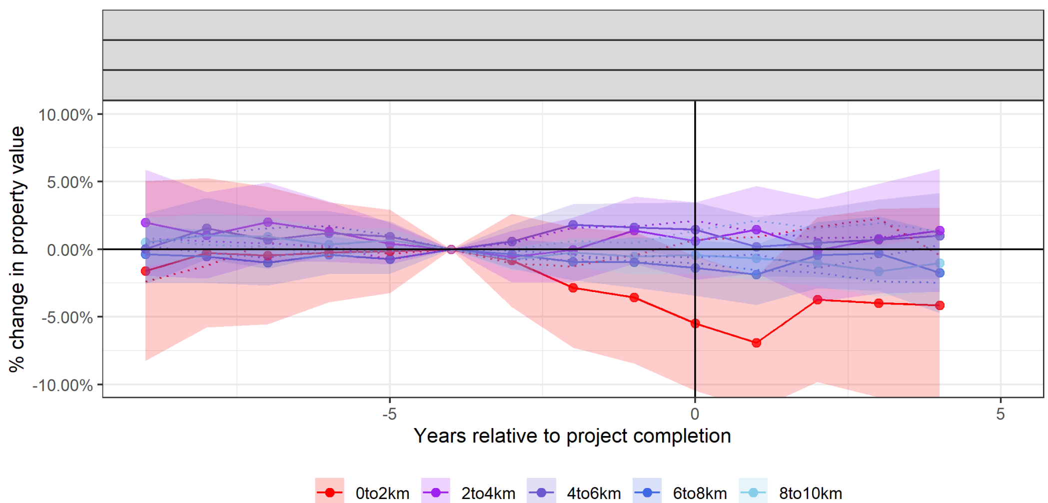
Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

3.3.2 Impacts on commercial property values

Wind projects

For wind projects the event study in Figure 3.8 provides some weak evidence of a possible impact on commercial property values in the closest 0-2km distance bin. This appears to be supported by the fact that the divergence with the effects for the failed projects is clearest for this closest distance bin. However, the more aggregated nature of the data on commercial rents means this analysis has less statisical power than was the case when looking at residential property values. This is reflected in the much wider confidence intervals. As such any negative effect is not consistently statistically different from zero.

Figure 3.8: Commercial Capitalization Event Study for Wind Projects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

Importantly, these results aggregate across all commercial property types. As such I repeat the analysis for four sub-sectors of commercial property types. Table 3.10 largely confirms the findings in the event study plot. There is a pronounced negative effect of around 4% in the 0-2km distance bin, but it is not statistically significant. To see what might be driving this I repeat the analysis for four sub-sectors of commercial property types. The specifications using the "other" sub-sector are indeed the ones with the largest effect sizes in the 0-2km distance bin. Even so, the sub-sector analysis still fails to find statistically significant effects.

Table 3.10: Commercial Capitalization for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Completed										
0to2km	−4.00	−0.90	1.33	−3.73	−6.00	−4.31	−3.91	2.43	−0.23	−5.57
	(2.59)	(3.17)	(4.08)	(4.94)	(3.30)	(2.90)	(3.36)	(4.14)	(6.27)	(4.14)
2to4km	0.43	1.23	0.68	7.84*	2.60	−0.52	−0.80	−0.14	−1.29	1.46
	(1.77)	(2.20)	(1.93)	(3.28)	(2.09)	(1.73)	(2.37)	(1.99)	(3.55)	(2.20)
4to6km	−0.43	−5.28**	0.65	−0.74	−3.13	−0.12	−4.12*	1.09	0.48	−3.49
	(1.36)	(1.68)	(1.66)	(2.52)	(1.55)	(1.32)	(1.57)	(1.75)	(2.50)	(1.57)
6to8km	−0.52	1.81	2.10	−2.23	1.34	−0.54	2.71	1.12	−4.36	1.83
	(1.13)	(1.56)	(1.53)	(2.21)	(1.39)	(1.15)	(1.51)	(1.41)	(2.27)	(1.43)
8to10km	−0.50	−1.49	−1.98	3.01	−1.89	−1.65	−3.99**	−1.94	−1.37	−2.18
	(0.92)	(1.33)	(1.16)	(1.77)	(1.15)	(0.93)	(1.26)	(1.24)	(1.79)	(1.22)
Failed										
0to2km	1.14	3.33	−1.94	3.23	3.19	1.69	1.18	−2.50	1.22	6.31
	(2.06)	(3.18)	(3.47)	(3.99)	(2.89)	(2.12)	(3.14)	(3.58)	(4.61)	(3.25)
2to4km	2.08	−1.42	2.20	1.06	0.94	1.05	−2.82	1.52	−0.59	−1.39
	(1.68)	(2.20)	(2.30)	(3.15)	(2.02)	(1.58)	(2.34)	(1.98)	(3.16)	(2.22)
4to6km	−1.37	−0.02	2.46	1.04	−1.40	−0.39	−1.53	1.92	1.17	0.91
	(1.33)	(1.86)	(1.79)	(2.59)	(1.53)	(1.19)	(1.67)	(1.74)	(2.35)	(1.45)
6to8km	−2.10	−0.63	0.94	−0.14	−0.75	−2.99*	−0.33	−1.30	−1.93	−3.63*
	(1.23)	(1.52)	(1.50)	(2.03)	(1.32)	(1.15)	(1.31)	(1.35)	(2.02)	(1.33)
8to10km	1.94	2.26	−0.46	−0.36	0.03	1.51	0.36	0.65	1.84	1.47
	(0.93)	(1.16)	(1.16)	(1.75)	(1.11)	(0.83)	(1.13)	(1.14)	(1.65)	(1.04)
R-Squared	0.94	0.94	0.96	0.92	0.90	0.94	0.94	0.96	0.92	0.90
N (millions)	0.20	0.12	0.09	0.06	0.13	0.20	0.12	0.09	0.06	0.13
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	–	–	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	Y	–	–	–	–
Industrial Sector	–	Y	–	–	–	–	Y	–	–	–
Retail Sector	–	–	Y	–	–	–	–	Y	–	–
Office Sector	–	–	–	Y	–	–	–	–	Y	–
Other Sector	–	–	–	–	Y	–	–	–	–	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Table 3.11 shows the results of the analysis using distance circles. The same general findings as with the pooled distance bins approach are evident.

Table 3.11: Commercial Capitalization for Wind Projects by Distance Circles

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, ,	−4.22	−2.19	−1.96	−1.54	-1.59^{*}
	(2.73)	(1.46)	(1.00)	(0.73)	(0.62)
Failed					
, ,	2.08	0.53	−0.48	−0.99	−0.11
	(1.67)	(1.11)	(0.78)	(0.64)	(0.52)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.09	0.13	0.17	0.20

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Lastly, table 3.12 shows the results of the analysis of differential effects for wind projects. Here again there is no consistent evidence of a statisically significant effect. Interestingly the properties with direct line-of-sight to appealed projects do have the largest reductions, and this is precisely the category we would expect to have the most pronounced effects.

Solar projects

For solar projects, Figure 3.9 shows the results of the event study, and it is clear that there is no noticeable change in property values when a nearby solar project is built.

Table 3.13 largely confirms the findings in the event study plot. There is no consistent pattern in the direction and magnitude of the coefficients, and the standard errors are consistently large when compared to the results for wind projects. Looking at the four sub-sectors of commercial property types also does not reveal any discernible trends.

Table 3.14 shows the results of the analysis using the distance circles approach. As before the same general results are evident as those found using the distance bins approach.

Lastly, table 3.15 shows the results of the analysis of differential effects for wind projects. Here again there is no consistent evidence of a statisically significant effect.

Table 3.12: Commercial Capitalization for Wind Projects with Differential Effects

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
Not Appealed, Not Visible, Deprived		2.88	−3.27	−1.47	−0.70
		(5.93)	(2.95)	(1.88)	(1.32)
Not Appealed, Not Visible, Not Deprived		−1.11	−3.68	−2.00	−2.92**
		(2.92)	(1.69)	(1.19)	(0.98)
Not Appealed, Visible, Deprived	−1.52	−2.22	−0.02	0.56	−0.65
	(5.29)	(2.64)	(1.78)	(1.27)	(1.05)
Not Appealed, Visible, Not Deprived	−5.18	−0.54	0.18	−1.59	−1.17
	(3.56)	(2.07)	(1.56)	(1.15)	(0.94)
Appealed, Not Visible, Deprived		4.45	1.57	−4.80	−4.70*
		(6.68)	(4.20)	(2.55)	(1.87)
Appealed, Not Visible, Not Deprived		−0.13	2.84	3.69	1.50
		(5.30)	(2.90)	(2.31)	(1.73)
Appealed, Visible, Deprived	−10.36	−7.03	−7.26*	−4.44	−3.62
	(6.18)	(3.12)	(2.57)	(1.98)	(1.70)
Appealed, Visible, Not Deprived	−2.08	−6.85	−2.74	−2.34	−3.81
	(6.11)	(3.74)	(2.48)	(1.88)	(1.86)
Failed					
Not Appealed, Not Visible, Deprived		−0.45	0.77	0.40	−0.04
		(2.83)	(1.70)	(1.29)	(0.87)
Not Appealed, Not Visible, Not Deprived		−3.36	−2.41	−1.23	−0.39
		(3.43)	(1.65)	(1.24)	(0.98)
Not Appealed, Visible, Deprived	1.01	0.61	−1.03	−1.42	0.79
	(2.25)	(1.70)	(1.32)	(1.03)	(0.84)
Not Appealed, Visible, Not Deprived	3.56	1.73	0.26	−0.71	0.17
	(2.55)	(1.83)	(1.19)	(0.99)	(0.85)
Appealed, Not Visible, Deprived		−2.83	2.18	0.87	1.55
		(6.28)	(3.11)	(2.22)	(1.66)
Appealed, Not Visible, Not Deprived		−3.69	2.48	1.48	1.67
		(4.69)	(3.39)	(2.36)	(1.96)
Appealed, Visible, Deprived	0.67	−0.08	−0.38	−3.81	−5.23**
	(6.68)	(3.23)	(2.00)	(1.90)	(1.79)
Appealed, Visible, Not Deprived	5.80	−4.53	−1.42	0.52	−0.64
	(5.92)	(4.10)	(2.81)	(2.02)	(1.77)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.09	0.13	0.17	0.20

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

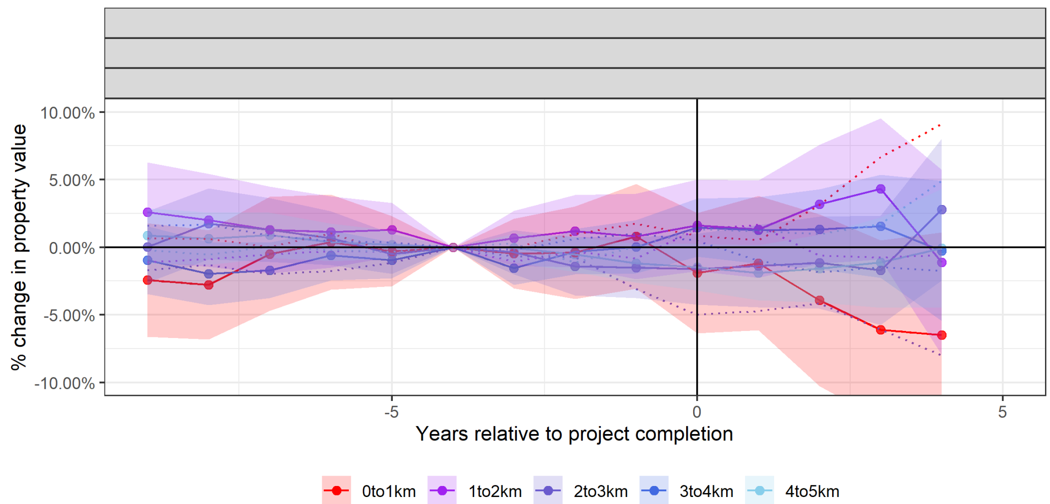
Table 3.13: Commercial Capitalization for Solar Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Completed										
0to1km	−3.44	−4.01	2.77	5.47	1.65	−2.80	−4.26	2.95	1.98	3.40
	(2.60)	(3.12)	(4.18)	(5.41)	(3.55)	(2.62)	(3.27)	(4.71)	(6.08)	(4.05)
1to2km	0.68	−0.29	−0.07	−3.57	−3.57	0.21	−2.29	2.66	−0.61	−2.37
	(2.17)	(2.98)	(3.69)	(4.41)	(2.76)	(2.11)	(2.82)	(3.73)	(4.50)	(2.82)
2to3km	−2.64	1.17	−1.07	−3.77	2.44	−1.26	1.35	−4.16	−1.85	0.83
	(1.78)	(2.48)	(2.56)	(3.66)	(2.11)	(1.48)	(2.23)	(2.37)	(3.62)	(2.15)
3to4km	2.40	−1.37	−0.13	2.87	−2.75	2.30	0.54	0.64	−1.01	−3.25
	(1.50)	(1.90)	(2.08)	(3.01)	(1.83)	(1.43)	(1.81)	(2.22)	(3.03)	(1.76)
4to5km	−1.46	−0.78	−0.81	−1.41	2.73	−1.82	−1.74	−2.21	−1.84	1.16
	(1.39)	(1.70)	(1.63)	(2.55)	(1.40)	(1.31)	(1.64)	(1.60)	(2.40)	(1.32)
Failed										
0to1km	2.40	6.22	−9.40	−5.01	−5.09	3.67	9.03	−14.51	−7.07	−4.25
	(2.77)	(3.68)	(6.37)	(5.44)	(4.19)	(3.16)	(4.03)	(7.19)	(6.12)	(4.93)
1to2km	−0.66	1.03	0.25	−6.94	−1.13	0.83	−0.89	−0.22	−2.52	−3.63
	(2.55)	(3.19)	(4.69)	(4.67)	(3.53)	(2.96)	(3.74)	(5.08)	(5.23)	(4.04)
2to3km	−3.13	−2.94	3.08	3.71	8.28**	−4.00	−4.97	1.89	6.51	11.49**
	(2.14)	(2.76)	(3.18)	(3.77)	(2.67)	(2.36)	(2.91)	(3.41)	(4.55)	(3.29)
3to4km	−1.26	−3.24	−2.57	−2.66	−3.53	−2.10	−0.75	−0.89	−5.48	−5.77
	(1.96)	(2.37)	(2.57)	(3.24)	(2.37)	(2.29)	(2.49)	(2.86)	(3.79)	(2.69)
4to5km	1.79	0.82	1.72	4.87	0.62	2.27	0.47	1.16	5.59	1.17
	(1.38)	(1.90)	(1.94)	(2.75)	(1.78)	(1.52)	(1.87)	(2.07)	(3.05)	(1.85)
R-Squared	0.94	0.94	0.96	0.92	0.90	0.94	0.94	0.97	0.92	0.90
N (millions)	0.21	0.13	0.09	0.06	0.14	0.21	0.13	0.09	0.06	0.14
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	–	–	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	Y	–	–	–	–
Industrial Sector	–	Y	–	–	–	–	Y	–	–	–
Retail Sector	–	–	Y	–	–	–	–	Y	–	–
Office Sector	–	–	–	Y	–	–	–	–	Y	–
Other Sector	–	–	–	–	Y	–	–	–	–	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Figure 3.9: Commercial Capitalization Event Study for Solar Projects



Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 95% confidence intervals.

Table 3.14: Commercial Capitalization for Solar Projects by Distance Circles

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, ,	-3.26	-1.91	-1.29	-0.87	-0.98
	(2.10)	(1.34)	(0.89)	(0.74)	(0.66)
Failed					
, ,	1.47	-0.27	-1.83	-1.35	-0.46
	(2.35)	(1.68)	(1.16)	(0.97)	(0.88)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.08	0.13	0.17	0.21

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

Table 3.15: Commercial Capitalization for Solar Projects with Differential Effects

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
Not Appealed, Not Visible, Deprived	−2.25	−1.88	−0.73	−0.51	−0.55
	(3.08)	(2.02)	(1.25)	(0.98)	(0.93)
Not Appealed, Not Visible, Not Deprived	−8.18	−4.05	−5.87**	−2.07	−0.97
	(6.08)	(2.95)	(1.90)	(1.42)	(1.07)
Not Appealed, Visible, Deprived	−3.41	−0.95	−2.22	−0.35	−0.31
	(2.58)	(1.56)	(1.15)	(0.98)	(0.87)
Not Appealed, Visible, Not Deprived	−0.42	−2.50	−0.74	−0.83	−1.58
	(4.46)	(2.40)	(1.68)	(1.61)	(1.40)
Appealed, Not Visible, Deprived	146.30	6.54	7.78	7.33	2.01
	(91.58)	(7.06)	(5.07)	(4.69)	(3.49)
Appealed, Not Visible, Not Deprived	−16.91	−8.41	1.66	−0.58	7.85
	(9.49)	(5.61)	(5.19)	(5.76)	(4.47)
Appealed, Visible, Deprived	−25.39**	−3.17	4.05	4.27	3.75
	(7.44)	(5.31)	(6.83)	(4.29)	(3.77)
Appealed, Visible, Not Deprived	16.54	−3.53	2.85	−1.26	2.07
	(11.36)	(8.06)	(5.20)	(6.38)	(5.44)
Failed					
Not Appealed, Not Visible, Deprived	−4.91	0.83	−2.75	−1.67	−1.21
	(4.02)	(2.28)	(1.69)	(1.40)	(1.21)
Not Appealed, Not Visible, Not Deprived	−0.71	−0.70	−0.66	−0.64	−2.10
	(6.73)	(3.93)	(2.26)	(1.70)	(1.67)
Not Appealed, Visible, Deprived	2.83	0.85	1.26	0.94	1.37
	(2.82)	(2.23)	(1.99)	(1.59)	(1.36)
Not Appealed, Visible, Not Deprived	−1.22	−2.46	−0.80	1.63	3.20
	(5.10)	(3.28)	(2.37)	(2.54)	(2.41)
Appealed, Not Visible, Deprived	12.31	6.46	3.09	1.67	−0.70
	(5.68)	(3.97)	(3.03)	(2.20)	(1.91)
Appealed, Not Visible, Not Deprived	−3.92	−11.63	0.68	0.45	−0.02
	(12.40)	(8.05)	(4.04)	(3.13)	(3.08)
Appealed, Visible, Deprived	1.03	0.51	2.97	−2.05	−3.26
	(5.03)	(3.42)	(3.09)	(2.80)	(2.40)
Appealed, Visible, Not Deprived	16.85	−0.51	2.83	−3.25	0.81
	(11.76)	(8.14)	(5.54)	(4.44)	(3.84)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.08	0.13	0.17	0.21

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Point estimates based on the event study specifications are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away.

3.4 Conclusions

In this paper I have estimated the local costs imposed by wind and solar projects, as measured by capitalization into nearby property values. I find that wind projects can have significant negative impacts on the surrounding area, primarily in the form of visual disamenity. This is captured by reductions in nearby residential property values.

The overall magnitude of the observed effects is broadly consistent with prior studies. Similar to Gibbons (2015) I also find that using geospatial methods to partition the effects by visibility shows that properties with direct line of sight do indeed have larger negative impacts from wind farms. Building on the work of Jensen et al. (2018) I find evidence that adding wind capacity does have a declining incremental effect, such that the first turbine built has a larger impact than the tenth or hundreth.

As well as confirming prior findings though, this paper provides a number of valuable additions. First, I show that any negative impacts are concentrated amongst properties in wealthier, less deprived areas. This fits with the fact that these properties are likely to derive a larger proportion of their value from environmental and neighborhood amenties such as pleasant views, historic buildings and unspoiled green space. All these amenities are the ones that a new wind project would be expected to adversely effect. The concentration of these negative local impacts in wealthier communities therefore has important distribution implications that are worthy of further study.

The use of planned but not approved projects is another valuable addition to the literature. As well as validating the negative effects found near completed projects, this part of the analysis has also highlighted the importance of potential sorting behavior, with property values actually increasing for areas near a project that did not go ahead. This confirms survey-based evidence of possible sorting set out by Hoen et al. (2019).

The analysis of solar projects is one of the first in the literature (Dröes and Koster, 2020). The finding of no significant effect is certainly consistent with the fact that these projects have tended to be less controversial than wind projects, at least in the UK context. This is not to say that solar projects have no impacts on local communities, and it may be that looking at even smaller distances may reveal statistically significant effects. However, in terms of economic significance, this study provides strong evidence that any such local impacts are likely to be small, at least when compared to wind projects. Further study of this particular technology would still be beneficial, especially given the major role solar power is expected to play in other parts of the world.

Lastly, the analysis of impacts on commercial property values here was largely inconclusive. On one level finding no significant effect is perhaps understandable given the aggregated nature of the data and the narrow range of commercial activities we might expect to be impacted. Nonetheless, this remains an area where other research is sorely lacking. A critical piece of further work will be to examine impacts on commercial property values at a more granular level.

Chapter 4

The economic costs of NIMBYism in renewable energy deployment

4.1 Introduction

Large infrastructure projects can create widespread societal benefits and are often critical to tackling major national or global challenges. A prime example is climate change mitigation and adaption, which will require large investments over the coming decades in areas such as renewable energy production, power grid infrastructure and public transit (IEA, 2018). However, large infrastructure projects such as these also create concentrated local impacts that can in turn lead to fierce lobbying during the planning approval process. This lobbying by local residents and businesses is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior and is thought to be common in a range of settings.

One area where the topic of NIMBYism has been debated extensively is renewable energy deployment.[1] Here a wealth of survey-based studies have examined the factors that determine community acceptance for wind and solar projects (Wolsink, 2000; Bell et al., 2013; Burningham, Barnett and Walker, 2015; Rand and Hoen, 2017; Hoen et al., 2019). Importantly though, the actual economic consequences of local opposition and its influence on the planning process remains poorly understood. There is some empirical evidence that local residents that oppose wind farms respond by voting the politicians re-

[1] NIMBYism can be more precisely defined as "the combined preference for the public good and a refusal to contribute to this public good" (Wolsink, 2000). The public good of interest here is the provision of renewable energy, with the aim of mitigating climate change and ensuring secure energy supplies, and the refusal to contribute is most clearly expressed by a locality's decision to deny planning permission for a proposed project.

sponsible out of office (Stokes, 2016), or by pushing for new zoning regulations constraining development (Winikoff, 2019). There is also some limited evidence that certain features of wind or solar projects may be associated with projects being more likely to be approved (Roddis et al., 2018), but whether this is resulting in insufficient or misallocated investment has yet to be studied. Research on housing development has shown that local planning restrictions can indeed result in chronic underinvestment that acts as a substantial drag on the economy (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019). Given the growing urgency of combating climate change, it seems plausible that similar impediments to the deployment of renewable energy could also impose large costs on society.

In this paper I estimate of the economic costs created by frictions in the planning process for renewable energy projects. For this I focus on the United Kingdom where I am able to draw on detailed planning data for all renewable energy projects, including information on projects that were not approved. The planning data allows me to credibly estimate the scale and distribution of impacts on local residents in the form of changes to nearby property values. I then link these local costs to the likelihood of projects gaining approval. The vast majority of wind and solar projects in the UK must be approved at the local level by county planning officials. This allows me to estimate how local officials weigh local impacts during the approval process, including how this compares to the weight they place on the other wider societal benefits of these projects (e.g., carbon emissions reductions).

Using my estimates of the local impacts of wind and solar projects I then examine how they influence the planning approval process. To do this I use data on the planning outcomes of roughly 3,500 wind and solar projects spanning almost three decades. For each project I estimate both the local impacts (e.g., on residential property values) and the wider societal impacts (e.g., the market value of the electricity produced, the external value of any emissions abated and the costs of constructing and operating the project). I then estimate which factors have a stronger effect on the likelihood of projects receiving planning approval. Here I find evidence that by far the most significant factor guiding local planning officials is indeed local property value impacts. This is consistent with the fact that wind projects are much less likely to be appoved than solar projects. Interestingly these effects are more pronounced in politically conservative areas.

That local officials pay attention to local factors is unsurprising. In fact, there is a compelling argument to be made that local policymakers are in fact making optimal private decisions for their respective jurisdictions. For instance, Greenstone and Moretti (2003) show how local government policies to attract new large manufacturing plants do actually increase the welfare of local residents in the form of increased employment and local tax revenues.[2] The key

[2]See Slattery and Zidar (2020) for a more recent review of the merits of these kinds of

here is that what may be optimal for a given local area may in aggregate create harmful outcomes for society as a whole. In the context of renewable energy, I find that refusing a renewable energy project to avoid adverse local impacts may indeed benefit local residents. However, the resulting underprovision of renewable energy or the shift in development to more remote, more expensive projects, raises the costs of climate change mitigation for society as a whole. This problem is particularly acute for wind projects as they are most clearly subject to misaligned planning incentives.

To quantify the potential scale of the problem and the scope for Pareto-improving trades, I identify the set of projects that would have produced the observed annual deployment of renewable energy at least cost to society. I find that failure to allocate investment in a more societally efficient manner has increased the cost of the UK's deployment of wind power by as much as £27 billion by 2019. Moreover, £20 billion of these foregone gains are from projects that were refused planning permission, indicating that the main driver of misallocated investment is the planning process. These frictions in the planning process are substantial, amounting to 25% of the lifetime capital and operating costs of all the wind projects built over this period. The equivalent misallocation in solar power has been much smaller at £0.3 billion, or less than 2%.

Of the potential gains from reallocating wind power investment, a substantial portion can be achieved by switching to wind projects that are cheaper to build and less remotely located, even though these create larger local impacts. This suggests that there are potentialy legitimate concerns around the impact of NIMBYism on planning outcomes.

Interestingly, the extent of concerns about the planning process, and NIMBYism in particular, depends heavily on the tradeoff between onshore and offshore wind. The UK's early investments in offshore wind power have been expensive, with large potential cost savings available from simply substituting toward onshore wind, even where this incurs larger local costs. Studying onshore and offshore wind separately causes the misallocated investment costs from the planning process fall to £7 billion, or around 10%, with a small fraction plausibly attributable to NIMBYism.

Importantly, the merits of this substitution between onshore and offshore wind depends heavily on the amount of learning and technological progress that has been created by the growing shift toward offshore wind. Where offshore wind learning has been substantial, NIMBYism may even have had the beneficial unintended consequence of pushing development offshore, driving down future costs for this nascent technology. Where offshore wind learning has been minimal, NIMBYism will likely have cost the UK dearly.

There may also be important gains to be had from ensuring the planning

local tax incentives in the US context.

process is better able to account for the declining incremental local impacts of adding additional wind capacity. Current planning outcomes tend to try and share the burden of renewable deployment across all jurisdictions, discouraging the concentration of capacity at larger projects in fewer areas. Reversing these tendencies could produce large gains. A key challenge here is addressing the distributional implications of these changes.

Policymakers have already tried a range of policies that would appear to address some of the undesirable planning outcomes identified here. These policies include direct payments to local residents in the form of community benefits funds, changes to tax regulations to allow more revenues from renewable energy projects to be kept locally, and efforts to encourage local ownership of renewable energy projects. My findings suggest the scale of these sorts of transfer mechanisms may have to increase significantly in some instances to remedy concerns about NIMBYism. Having a more explicit process for providing compensation payments to affected local communities could also yield real benefits. This includes finding ways to make transfers across jurisdictions to incentivize some areas to host more concentrated deployment of renewable energy projects.

The findings in this paper have important policy implications both in the energy sector and beyond. Rapidly growing global demand for electricity and concerns about climate change mean that a further $20 trillion in new power plant investment is expected by 2040, mostly in renewable sources (IEA, 2018). The findings in this paper suggest that this expansion could be achieved at much lower cost if more care is taken when incorporating the impacts on local communities into the process. Finally, energy infrastructure projects such as those studied here share many similarities with other major infrastructure projects, such as roads, railways, airports, landfill sites, water and waste treatment works, and so on. There is every reason to think that NIMBYism presents a similar problem in those sectors as well, and so exploring the gains elsewhere remains a fruitful area for further research.

4.2 Empirical Strategy

To examine the planning process I conduct three pieces of analysis. First, I quantify the various costs and benefits of each project. The goal is to understand how large the local impacts are relative to various non-local factors that are the reason for pursuing renewable energy in the first place. Second, I conduct a regression analysis to understand how sensitive planning officials are to local versus non-local impacts. Third, I conclude by estimating the potential costs created by the planning process in the form of misallocated investment.

4.2.1 Project planning applications

Despite a relatively broad political consensus in the UK on the importance of tackling climate change, the expansion of renewable energy has still been uneven and contentious. Both wind and solar projects have historically been dependent on carbon taxes and production subsidies, both of which are set at the national level. In the 1990s and 2000s the vast majority of support went to onshore wind, in part because this was the most well-established technology at the time. In 2009 and 2010 a number of reforms were introduced that supported the rapid expansion of both solar power and offshore wind. In 2015 a new Conservative government made a number of major changes that led to a significant decline in new investment for both solar power and onshore wind. These changes included freezing the UK carbon tax, cutting the funds available to solar power and blocking future onshore wind farms from receiving any subsidies. In the case of onshore wind these policy changes were driven in part by the vocal opposition of rural voters to wind turbines. Their views were echoed by the then-prime minister David Cameron who vowed to "rid" the countryside of these "unsightly" structures. Interestingly offshore wind was not subjected to the same hostile policy environment, perhaps because these projects tend to be located a long way out at sea. In 2020 the moratorium on subsidies for onshore wind was lifted, in part due to waning opposition from Conservative voters.

Besides shifting national politics, arguably the most important determinant of the deployment of renewable energy is the planning approval process. In the UK the overwhelming majority of applications for planning permission are managed by local planning authorities. These local authorities are the primary unit of local government in the UK and on average cover around sixty thousand households.[3] Project developers submit a planning application to the relevant local planning authority. The local planning authority considers the merits of the proposal in line with national and local planning guidelines. A public consultation period is required where affected stakeholders have the opportunity to provide comments. The local planning authority then decides to either approve or refuse the planning application.

In making their determinations local planning authorities must weigh a range of competing factors. Planning authorities have a legal duty under the 2008 Planning Act to mitigate and adapt to climate change. However, the national guidelines are relatively open-ended, stating that "all communities have a responsibility to help increase the use and supply of green energy, but this does not mean that the need for renewable energy automatically overrides environmental protections and the planning concerns of local communities". In considering any issues raised by local stakeholders, planning guidelines emphasize the importance of promoting renewable energy, the suitability of the local

[3]This means UK local authorities are broadly analogous to US counties.

area for the technology being proposed, and the impact (both individually and cumulatively) on the character of the surrounding landscape, especially where this affects nearby heritage assets of cultural significance (e.g., churches, castles and monuments), national park designations, or sites of environmental significance. In many cases EU law requires that applicants conduct an environmental impact assessment. For wind projects there is also a requirement to conduct a noise assessment, as well as a number of safety standards to ensure the proposed turbines do not interfere with flight paths or radar installations. Beyond these requirements there is a general preference against strict criteria or zoning (e.g., setbacks, buffer zones or quotas). However, there is scope for planning authorities to seek amendments to planning applications, or approve them with certain conditions aimed at mitigating potential concerns that may have been raised.

There are two main exceptions to local control of the planning process. The first arises when projects are sufficiently large that they are deemed to have substantial national or regional importance (e.g., motorways, airports, rail networks, ports etc.). In these situations the planning decision is made by the national Planning Inspectorate, and any directly affected local authority is included as a statutory consultee to the process. In the case of renewable energy, projects with a capacity greater than 50MW have historically been deemed to be of national significance. However, as part of the reforms introduced by the Conservative government of 2015 this threshold was removed for onshore wind projects such that all subsequent projects would be considered at the local level irrespective of size. The second exception to local control arises when a developer appeals the decision of a local planning authority. Once an appeal is lodged the national Planning Inspectorate conducts a review and decides to either uphold or overturn the initial decision. In both cases the split between local and national control provides an interesting opportunity to examine how decisionmakers at these different scales weigh planning applications.

To help document the impact of the planning process on the deployment of renewable energy, the UK government maintains and publishes a database on the planning applications for all major renewable energy projects that have been proposed since 1990. Figure 3.1 shows where these projects have been located and when they were submitted for planning approval. Table 4.1 provides a range of additional summary statistics on outcomes from the planning process for wind and solar projects as documented in the planning database.

The projects covered in the planning database comprise the overwhelming majority of wind and solar capacity in the UK, and so many of the trends described earlier are evident in Figure 3.1. There is a roughly even split of projects across the two technology types, although wind projects are larger on average and so account for the vast majority of total renewable capacity. Despite this, it is noticeable from Table 4.1 just how much tougher the planning process is for wind projects. Recieving a planning decision takes three to four

Table 4.1: Summary Statistics on Project Planning Outcomes

	Solar	**Wind**
Number of Projects	1675	1775
Total Capacity (MW)	13737	58618
Average Capacity (MW)	8.2	33.0
Length of Planning Process to Initial Decision (days)	143	545
Length of Planning Process to Final Decision (days)	184	643
Initial Decision Approval Rate	0.724	0.391
Share of Projects subject to National Authority Decision	0.001	0.128
National Authority Initial Decision Approval Rate	1.000	0.648
Local Authority Initial Decision Approval Rate	0.723	0.353
Share of Projects Appealed	0.123	0.230
Appeal Success Rate	0.461	0.460
Final Decision Approval Rate	0.779	0.490

Notes: This table contains summary statistics for all wind and solar energy projects in the UK with a capacity of 1MW or greater. This excludes projects that are under review at the time of writing. Projects can be subject to approval by either a local or national planning authority. The planning authority makes an initial decision to either approve or refuse the project. Projects may then be appealed in which case the final decision may differ from the initial decision.

times longer for wind projects. The approval rate is much lower as well, with 39% of wind projects being approved compared to 72% for solar projects.

Interestingly, Table 4.1 provides suggestive evidence that national planning decisionmakers are more positively predisposed to renewable energy projects and perhaps less influenced by local political considerations. This is reflected in the higher approval probability for projects decided at the national level. This is also further demonstrated by the impact of the appeals process. In total just under 600 projects were subject to an appeal, representing roughly 10GW of capacity. A larger proportion of these are wind projects, consistent with their higher likelihood of refusal. The appeal success rate is 46%, giving a roughly even split between projects that were upheld on appeal and projects that were overturned on appeal. Accounting for appeals means the final planning approval rates increase to 49% for wind projects and 78% for solar projects.

I provide further information on some of the key reasons why projects are refused by collecting the planning decision letters for a sample of projects. Based on the refusal decisions of 120 wind and solar projects I find that by far the most cited reason is the visual impact of a project on nearby residents and the overall character of the surrounding landscape. Visual impact reasons were mentioned in 60% of solar refusals and 75% of wind refusals. The next most common are a related set of concerns about the proximity of a project to culturally important heritage sites. Heritage concerns were mentioned in 30% of solar refusals and 50% of wind refusals. Unsuprisingly, noise concerns do not appear in any of the solar refusals. Interestingly though, noise concerns do not feature particularly heavily for wind projects either, with only 25%

mentioning noise as a reason for refusal. This may seem puzzling at first given the noise from rotating turbine blades is widely considered to be a major local impact of any wind project. It may simply be that, whilst important, noise impacts are still small relative to visual disamenities. However, the lack of refusals due to noise concerns might also be driven by the fact that there are already clear objective regulations for noise limits, and so developers are likely to ensure these are met for all proposed projects. Visual impacts are harder to explicitly include in planning procedures and so provide far greater latitude for subjective interpretation by local decisionmakers.

The planning outcome data described here makes clear that a major challenge for the deployment of renewable energy is gaining the backing of local residents and firms. In many ways this makes renewable energy projects similar to most other large-scale projects, and so the findings here may be instructive for other kinds of infrastructure. However, the particular importance of national and global factors (e.g., climate change) makes wind and solar projects a particularly challenging case when planning processes are so dominated by local decisionmakers. Unlike more traditional local infrastructure projects like transport or housing, most of the benefits of wind and solar projects are spread diffusely throughout wider society whilst many key costs remain concentrated locally. The risk here is that, in the absence of some kind of direct payments, local decisionmakers are unlikely to put much weight on benefits accruing to non-local actors. This paper will assess the extent of the costs posed by these misaligned incentives.

4.2.2 Estimating local project costs and benefits

I calculate the total local impacts of wind and solar projects using estimates of the capitalization into local property values. To calculate this I start with hedonic estimates of how the construction of a nearby project translates into a percentage change in the value of a given property. I then multiply these treatment effects by the total value of all properties near each project.

Capitalization effect assumptions

To estimate the local impacts of wind and solar projects I use the capitalization into local property values. The rates of capitalization I examine are primarily based on the treatment effects from my own analysis, combined with other comparable estimates in the literature. The assumed effects for residential property values are shown in Table 4.2. Impacts on commercial rents are not explored given the inconclusive nature of my earlier findings and the lack of any alternative studies.

For wind projects my analysis found that at 10MW wind project leads to a roughly 3% reduction in residential property values at distances of 0-2km. Effects are smaller at 2-4km, roughly around 1.5% depending on the specification. Beyond 4km it seems plausible that the effects have largely decayed to zero. These numbers seem broadly consistent with other studies. For instance, estimates from Jensen et al. (2018) imply that a similar 10MW project should also lead to a roughly 2% decrease in residential property values within 3km. Similarly, Dröes and Koster (2020) find that turbines lead to a 2.5% reduction for properties less than 2km away, rising to 5% for larger turbines. Table 4.2 shows that the central case mirrors these broad effect sizes.

My analysis also finds some limited evidence that effects are larger for properties with direct line-of-sight, although this evidence is mixed and only emerges clearly when looking at appealed projects. In this case the effect on a visible property at 0-2km rises to 6%. This seems consistent with the findings from Dröes and Koster (2020) regarding the increased impact of larger - and presumably more visible - turbines. Similarly, (Gibbons, 2015) finds more pronounced effects for directly visible properties, with those located within 2km experiencing reductions of 5-6%. To capture these more pronounced effects due to direct visibility, Table 4.2 shows that the assumed effects for visible properties are twice as large as those for non-visible properties.

Lastly, my earlier capitalization analysis also extended on any prior research in examining the impacts on property values for comparable areas where projects were proposed, but ultimately did not go ahead. Beyond finding a null effect in these areas, I actually found some evidence of an appreciation in property values. The exact drivers of this are unclear, but it might plausibly be the result of some kind of sorting behavior. Conventionally any treatment effects from a new wind project are taken as the estimated effect on properties near completed projects. However, there is a possible argument for calculating the overall treatment effects by taking the difference between the reductions in areas near completed projects and the increases in areas near abandoned projects. This would have the effect of almost doubling the final treatment effects from wind projects. I do not explore this approach directly, but instead try to allow for the possibility of these larger effects with the "high" sensitivity case shown in Table 4.2.

For solar projects I do not find any clear evidence of an effect on residential property values. At best I can rule out the possibility of either large positive or large negative effects. There is also a lack of other studies that have examined this question. Dröes and Koster (2020) do suggest there is evidence of a 3% reduction in property values within 1km of a solar project. However, the sample size for their analysis is very small and so they acknowledge the evidence for this is weak. To reflect this my central case assumes the impact is indeed zero. However, to explore the possibility of both positive and negative effects the "low" and "high" sensitivity cases shown in Table 4.2 allow for impacts on the order of 1.5% either way within 1km.

Table 4.2: Assumptions on Residential Property Capitalization Effects

Technology	Distance	Visible	Deprived	Effect (Low)	Effect (Central)	Effect (High)
Wind	0-2km	Yes	Yes	-0.5%	-1%	-2%
Wind	0-2km	Yes	No	-2%	-4%	-8%
Wind	0-2km	No	Yes	-0.25%	-0.5%	-1%
Wind	0-2km	No	No	-1%	-2%	-4%
Wind	2-4km	Yes	Yes	-0.25%	-0.5%	-1%
Wind	2-4km	Yes	No	-1%	-2%	-4%
Wind	2-4km	No	Yes	-0.125%	-0.25%	-0.5%
Wind	2-4km	No	No	-0.5%	-1%	-2%
Solar	0-1km	Yes	Yes	0.25%	0%	-0.25%
Solar	0-1km	Yes	No	1%	0%	-1%
Solar	0-1km	No	Yes	0.125%	0%	-0.125%
Solar	0-1km	No	No	0.5%	0%	-0.5%
Solar	1-2km	Yes	Yes	0.125%	0%	-0.125%
Solar	1-2km	Yes	No	0.5%	0%	-0.5%
Solar	1-2km	No	Yes	0.0625%	0%	-0.0625%
Solar	1-2km	No	No	0.25%	0%	-0.25%

Notes: This table contains the assumed values for the capitalization of a wind or solar project into the value of a nearby residential property. Values shown are the equivalent % change in property values for a 10MW project. The actual logarithmic coefficients can be calculated by dividing these values by ln(10).

Value of local property

To construct a panel dataset of the total value of all properties in the UK I start with more aggregated data on property values, rents and counts at the local authority level. I then downscale these to the postcode level for residential properties and the LSOA level for commercial properties. This downscaling is based on a range of data, including the residential property transactions and average commercial rents data used in the prior hedonics analysis. Full details can be found in the appendix.

To estimate of the total value of all residential properties near each project, the transactions data used earlier is not quite suitable for this task. This is because it does not include all properties, and for the properties it does include it only has values at the time of sale, rather than in each year. To remedy this and construct a panel of total residential property values at each post code I start with a range of more aggregated data and then downscale these to the post code level.

For residential property prices I start with annual average prices published by the UK Office for National Statistics (ONS) at the local authority level. The averages themselves are constructed based on the same transaction data from HMLR used earlier. The main difference is that they correct for the overall composition of the housing stock, as well as extending the coverage to include equivalent values for Scotland based on separate property-level data held by the National Registers of Scotland (NRS). To downscale the average property prices to the post code level I fit a predictive model that allows me to estimate how house prices in a given post code vary relative to the local authority average.

To be more explicit, when conducting this downscaling exercise I fit a predictive model based on other data that is correlated with prices whilst also being consistently available at the post code level. This includes measures of whether a post code is rural or urban, index scores of social deprivation, census data on the socioeconomic status of residents and geospatial data on terrain and landcover. I then use the transaction-level data for England & Wales from HMLR to fit a predictive model that maps these covariates into residential property values. I then construct a house price index for all postcodes using the predictions from this model. Finally I downscale the local authority annual average prices using this predictive index to get an equivalent set of annual average residential property prices at the postcode-level that also remain consistent with the original local authority values.

In order to get total residential property values I then combine these average prices with data on the number of residential properties. Here I use data on counts of properties at the local authority level from the VOA for England & Wales and from the NRS for Scotland. To downscale the property counts I proportionally allocate the total number of properties in each local authority based on census data of the number of households in each post code. The result is a panel of average prices and property counts for each post code over the entire period of interest.

The process of estimating the value of all commercial properties near each project is more straightforward. The same LSOA data from the VOA that was used in the capitalization analysis is sufficient for England & Wales in that it provides both average values and numbers of commercial properties for each LSOA. I supplement this with comparable data for Scotland from the Scottish Government's Local Government Financial Statistics. These are at the more aggregated local authority level but are otherwise equivalent in that they include both average values and numbers of commercial properties. As with the residential property values I once again conduct a downscaling exercise using the same approach set out above.

4.2.3 Estimating non-local project costs and benefits

The next step requires estimating the various non-local costs and benefits associated with each renewable energy project. The primary costs and benefits estimated here are: 1) the market value of the electricity produced, 2) the value of any carbon emissions abated, 3) the value of any local pollution emissions abated, 4) the capacity value from contributing to supply security, 5) the capital construction costs of installing the project, 6) the operation and maintainence (O&M) costs incurred over its lifetime, and 7) the benefits of learning-by-doing.

There are undoubtedly other secondary costs and benefits created by these projects not included here. For instance, the employment benefits from building and maintaining the project are not included here. In general though these should be minimal for wind and solar projects. For instance, Costa and Veiga (2019) find evidence of a small temporary boost to employment from wind projects during the construction phase, but no lasting impact on employment beyond that. I confirm this using employment data and the results can be found in the appendix. Even so, the included costs and benefits are not exhaustive and this should be kept in mind when interpreting the results presented later.

Each of the costs and benefits I do estimate are still subject to significant uncertainty, particularly those that are more challenging to quantify like the benefits of learning-by-doing. To deal with this I examine additional low and high sensitivities for some of the most uncertain categories. A final source of uncertainty is the discount rate used when converting everything to present value levelized quantities. Here again I examine a baseline real discount rate of 3.5% in line with UK Treasury guidance, as well as low and high sensitivities of 1.5% and 7% respectively.

To keep the analysis tractable I treat each project as if it is "on-the-margin" and being considered in isolation. The alternative would be to consider many projects in aggregate or treat larger projects as non-marginal. Doing so would require making complex alternative assumptions about equilibrium electricity prices or project costs, which is beyond the scope of this study. Treating each project as a marginal project also has the added benefit of mirroring the government's general approach to valuation, which in turn should be consistent with the valuation guidance that planning officials should be following when considering these projects.

An important limitation to the valuation undertaken here is that the data and approaches used are necessarily based on our current understanding, which may be quite different from the state of knowledge available to decisionmakers at the time they were considering a project. Moreover, the use of a mixture of observed historical data pre-2020 and forecasted data post-2020 is also slightly incongruous. In reality, any decisionmaker appraising a project would be relying exclusively on forecasts made at the time, or even sometime in the past. Fully tackling these issues would involve assembling a dataset of the same set of key inputs for all past years going back to 1990. This kind of exercise is potentially a paper in its own right, and it is not clear that it would even be feasible to locate the necessary data at this point. As such I continue to use values based on current knowledge and methods, but the limitations of this should be kept in mind when considering the results presented later.

Capacity factors

To estimate the main benefits of the electricity produced by a wind or solar project (items 1 to 3) requires estimating the amount of electricity a project will produce over its lifetime. Electricity production for wind and solar projects is almost entirely determined by three factors: the available wind or solar resource, the capacity of the project and the characteristics of the turbines or panels installed. A key statistic for summarizing the output from any renewable energy project is the capacity factor: the average amount of power the project produces normalized by the maximum power output capacity. In the UK this is generally around 30% for wind projects and 10% for solar projects.

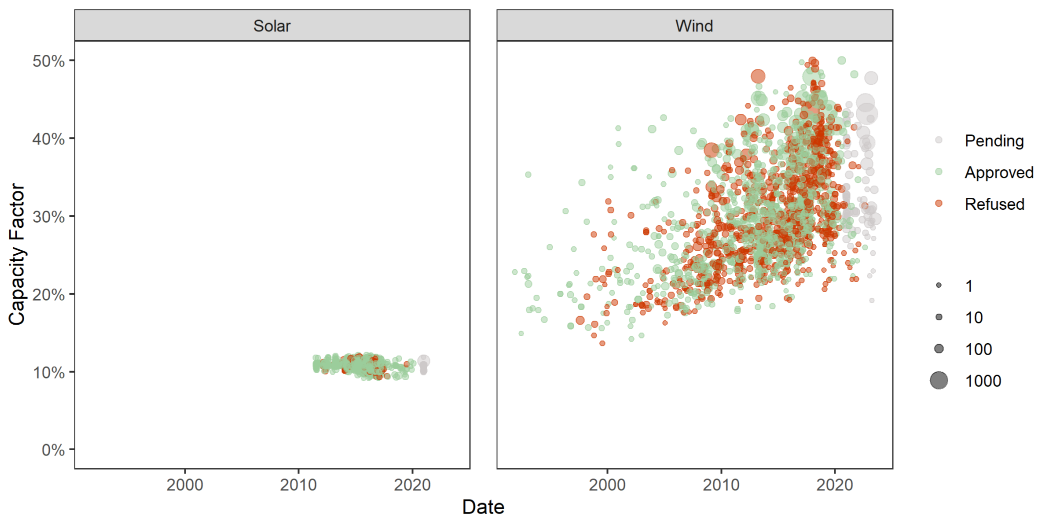
To estimate the capacity factors at each project I start with estimated capacity factors based on geospatial data. For solar projects I use the photovoltaic power potential estimates from the World Bank Solar Atlas. This provides estimated solar power productions profiles on a 1km grid for a representative solar installation. I use the coordinates of each project to extract the nearest solar production profile from this grid.

For wind projects the capacity factor is much more heavily dictated by the kind of turbine installed. To account for this I use data from Renewables Ninja. Here a user can select a set of location coordinates, a wind turbine model and a hub height, and then Renewables Ninja will calculate a wind power production profile that accounts for the characteristics of the turbine and the wind conditions in the specified location. For each wind project I first assign a likely turbine model from the list of possible turbine models in the Renewables Ninja database.[4] I then use the location coordinates of each project to extract an hourly power production profile from Renewables Ninja, which I then collapse to a single average capacity factor value.

Lastly, I collect data on country-level annual average capacity factors from the International Renewable Energy Agency (IRENA). I then use the IRENA data to normalize my initial project specific estimates. This allows me to ensure the original IRENA annual averages are maintained. The results are shown in Figure 4.1.

[4]To do this I start with the data on turbine manufacturers and models in The Wind Power Database (Pierrot, 2019). I match these to the turbine models available in the Renewables Ninja database. For each project in the planning database I calculate both the turbine capacity (in MW) and the turbine power density (in MW per m^2 of blade swept area). For each project I then find the closest turbine model on these two metrics that is also in the Renewables Ninja database. Where possible I prioritize selecting turbine models that have been more commonly installed in the UK.

Figure 4.1: Estimated Project Capacity Factors



Notes: This figure shows the estimated project capacity factors over time. Project sizes are determined by their capacity (in MW). Projects are classified by their development status. "In Review" are projects that have submitted a planning application but have yet to receive a final decision. "Successful" are projects that have been approved and are either awaiting construction, under construction, operational or have been subsequently decommissioned. "Unsuccessful" are projects that were refused planning permission or were otherwise withdrawn or halted.

Market value of renewable electricity

To value the electricity produced by each project I rely on data from the UK government's guidance on cost benefit analysis and the valuation of climate change policies. This primarily draws on data published by the Department for Business, Energy & Industrial Strategy (BEIS) and the Department for Environment, Food & Rural Affairs (DEFRA). The relevant data includes historical values for key inputs like electricity prices, the social cost of carbon and monetary damages from local pollution emissions. Projections of these inputs out to 2050 are made based on the UK government's modeling of the future electricity grid. Where data is missing or projections are not available I interpolate and extrapolate based on a range of additional industry sources.

I measure the market value of the electricity produced by each project (item 1) using the prevailing wholesale price of electricity. The values for annual average wholesale electricity prices are taken from the UK government's guidance on cost benefit analysis and the valuation of climate change policies. Pre-2020 the electricity prices are based on observed traded wholesale market prices. Post-2020 the electricity prices are based on projections out to 2050 that were made based on the UK government's modeling of the future electricity grid. This modeling includes forecasting fuel prices, demand and investment in new capacity, and then running a dispatch model to solve for clearing market prices. The guidance includes a set of "low", "medium" and "high" scenarios which I use to form my own "low", "medium" and "high" sensitivities for this particular impact.

Wind and solar projects do also receive production subsidies in addition to any wholesale market revenues.[5] I do not include subsidy revenues in my estimates of the market value of the electricity produced because from the perspective of a social planner they are simply transfers. However, these subsidies may be of interest from a developer perspective, or even for county officials in the event that local royalties and taxes are based on the total revenues a project receives. As such I do separately estimate the value of the subsidies each project using data from BEIS and Ofgem.

In valuing the electricity produced by a project I almost exclusively do so in terms of annual average marginal values. In reality there is significant temporal variation in the output from wind and solar resources, the price of electricity, the emissions intensity of marginal generation, and even line losses; all of which can affect the overall value of renewable energy production (Borenstein and Bushnell, 2018; Callaway, Fowlie and McCormick, 2018*b*). Fully simulating these dynamics at an hourly level is beyond the scope of this paper. I do still capture some of this variability through the calculation of capacity value (item 4), which reflects the contribution a project makes

[5]The main renewable subsidy programs over this time period are the Non-Fossil Fuel Obligation, the Renewables Obligation, Feed-In-Tariffs and Contracts for Difference.

to reliably matching demand, particularly during peak demand periods when supply is tight. Beyond this it seems reasonable to assume that, to a first order, annual averages should be sufficient for the purpose envisaged here, especially given the focus on the value of projects over their entire lifetime.

External environmental benefits

The electricity produced by renewable projects has added non-market benefits when it displaces other forms of environmentally harmful power production. In particular, where increased production of renewable electricity displaces coal or gas-fired power plants it will reduce both carbon emissions (item 2) and local pollutant emissions (item 3).

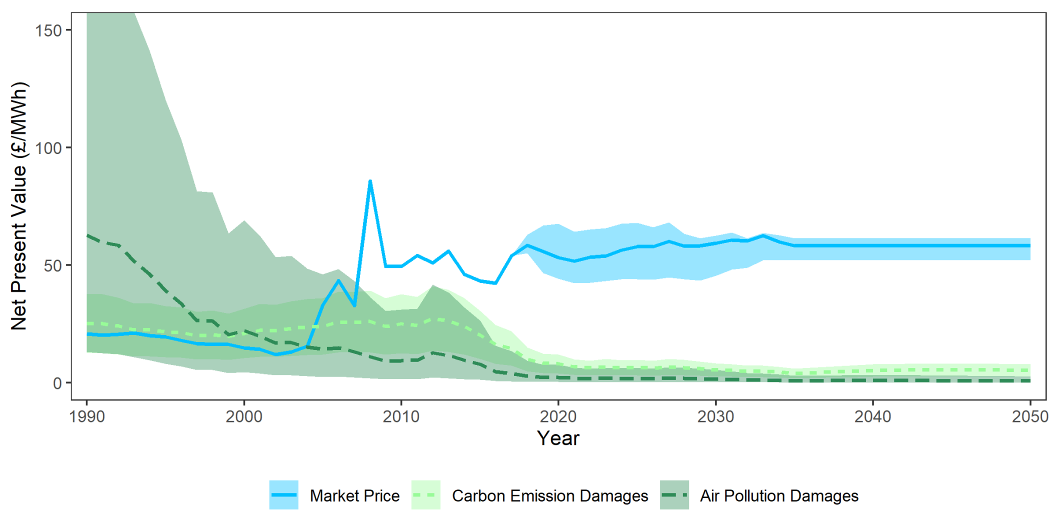
To calculate the amount of emissions abated I start with historical data on annual total electricity generation by source from BEIS and annual emissions by source from DEFRA. I use this to calculate annual average marginal emissions factors for CO_2, SO_2, $PM_{2.5}$, PM_{10} and NO_X assuming that either coal or natural gas has been the marginal source of generation. I then project these marginal emissions factors forward to 2050 assuming they decline in line with the forecast average carbon emission intensity of the total generation mix. These forecasts are again taken from the UK government's modeling of the future electricity grid.

Marginal abated carbon emissions are then valued using the UK values for the social cost of carbon and local pollution damages. In the 2019 guidance the central values are £68/ton for CO_2, £7,612/ton for SO_2, £128,415/ton for $PM_{2.5}$, £82,442/ton for PM_{10}, and £7,521/ton for NO_X. The resulting marginal values per MWh of electricity produced are shown in Figure 4.2 alongside the wholesale price of electricity. Once again the guidance includes a set of "low", "medium" and "high" scenarios which I use to form my own "low", "medium" and "high" sensitivities for these two impacts.

Capacity value

The capacity value of a power project (item 4) reflects the contribution it makes to reliably matching demand, particularly during peak demand periods when supply is tight. For intermittent power sources like wind or solar this is generally thought of in relative terms by starting with the capacity value of a conventional dispatchable generator (e.g. a natural gas-fired power plant) and then calculating "the proportion of installed renewable capacity that is able to 'displace' conventional generation or support extra demand while maintaining system reliability levels" (Harrison et al., 2015). Statistical modelling for the UK indicates that at present a wind project can expect around 10-20% of its capacity to provide this kind of reliable "firm" supply, whilst for solar the

Figure 4.2: Marginal Market and Non-Market Values of Renewable Electricity Production



Notes: This figure shows the changing marginal value of renewable electricity production over time. “Market Price” refers to the private value of the electricity produced as captured by wholesale electricity prices. “Carbon Emission Damages” refers to the external value of the CO2 emissions abated by displacing generation from other sources. “Air Pollution Damages” refers to the external value of the local pollution emissions abated by displacing generation from other sources. The lines are based on the UK government’s central scenario values and the shaded areas are bounded by the low and high scenario values.

equivalent number is as low as 1%. These percentages are sometimes referred to as "equivalent firm capacity" de-rating factors. The values for the UK reflect the fact that peak demand periods in the UK occur on winter evenings, and so whilst there is a decent probability the wind will be blowing at this point, the sun will almost certainly have set.

My starting point for is National Grid's recently published guidance on the de-rating factors they will use for the upcoming UK capacity market auctions. For the upcoming auctions in 2020 they have settled on de-rating factors of roughly 8.5% for onshore wind, 13% for offshore wind, and 1.5% for solar. Importantly though, these values can and will change over time. In particular they will tend to fall as the generation share of wind or solar increases, and tend to rise as demand shifts towards periods when the wind is blowing or the sun is shining. This is particularly important to capture for wind power because this is expected to provide such a large portion of the UK's electricity supply by 2050.

To capture the temporal variation in de-rating factors for wind projects I therefore rely on estimates by (Harrison et al., 2015) - namely those shown in Figure 11 in their paper. Their analysis examines how de-rating factors for onshore and offshore wind vary as the total wind power capacity in the UK increases. I converted this to points in time using information on the past and forecast growth of wind capacity from National Grid. Based on this, onshore wind de-rating factors were around 20% in 1990, but have fallen to 9% today, and will likely reach 7% by 2050. Offshore wind de-rating factors were likely as high as 35% in 1990, but have fallen to 15% today, and will likely be as low as 9% by 2050. I assume solar de-rating factors remain at 1.5% across the entire period.

To get the capacity value of each wind or solar project I multiply the relevant "equivalent firm capacity" de-rating factor by the capacity of each project and then value the remaining "firm" capacity based on the UK government's capacity market guidance. The result is a capacity value for each project in £/MW/year.

Capital and operating costs

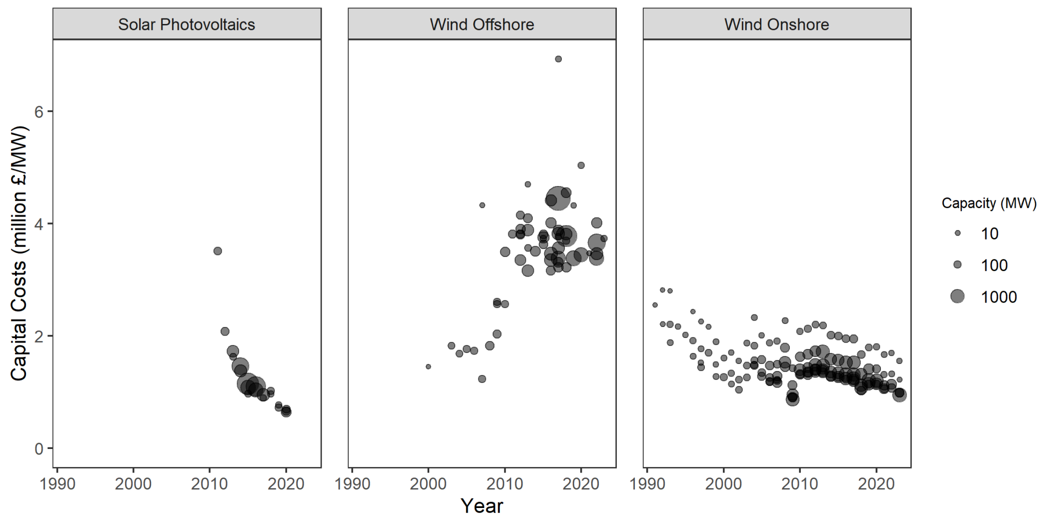
To calculate project specific estimates of installed capital costs (item 5) I rely primarily on data from IRENA. Unfortunately it is particularly challenging to get detailed project-level data on costs as this is usually treated as commercially confidential. The data provided by IRENA are country-level annual average installed capital costs for onshore wind and solar projects and so for these projects I use the UK values. For offshore wind IRENA only publishes global average values, although given the UK makes up such a large portion of offshore wind projects these values are a decent approximation of costs for the UK. Moreover, given the relatively small number of offshore wind projects I supplement this part of the analysis with direct project specific estimates of offshore wind costs taken from various industry sources. In all cases I convert these to consistent £/MW capital costs. I then make an additional adjustment to account for variation in costs due to economies-of-scale. There is evidence that large projects have consistently lower per MW capital costs than small ones. To capture this I use additional US data from Lawrence Berkeley National Laboratory (LBNL) on relative costs by project size. For example, they show that the per MW capital costs for a 50MW solar project are 10% lower than those for a 5MW solar project. The difference is even more pronounced for wind projects where the equivalent cost reduction is 35%. As such I use the LBNL data to ensure large projects have appropriately lower per MW capital costs than small ones. After making this adjustment I once again normalize the estimated per MW capital costs to ensure the original IRENA annual averages are maintained. Lastly I multiply by the capacity of each project to get project-level values for total installed capital costs.

To calculate project specific estimates of ongoing O&M costs (item 6) I also rely primarily on data from IRENA to capture general trends over time. Here no UK specific data is available and so for onshore wind I use US values whilst for solar I use the global values that IRENA applies to projects in OECD countries. In both cases I convert these annual averages to consistent £/MW/year values and compare to UK government estimates to ensure they seem reasonable. For offshore wind I assume the O&M costs are twice those of onshore wind to capture the increased costs of servicing turbines out at sea, again consistent with UK government estimates. An important additional contributor to O&M costs are grid connection and transmission use charges. These costs can vary substantially depending on the location that a wind or solar project is connected to the grid. To capture this I modify the average O&M costs based on transmission system charging data from National Grid. This ensures that projects connecting to the grid in remote regions have appropriately higher costs than projects located close to demand centers.[6] This includes accounting for the additional grid infrastructure costs associated with the offshore wind.[7] See the appendix for full details. Finally I once again multiply by the capacity of each project to get annual project specific estimates of O&M costs.

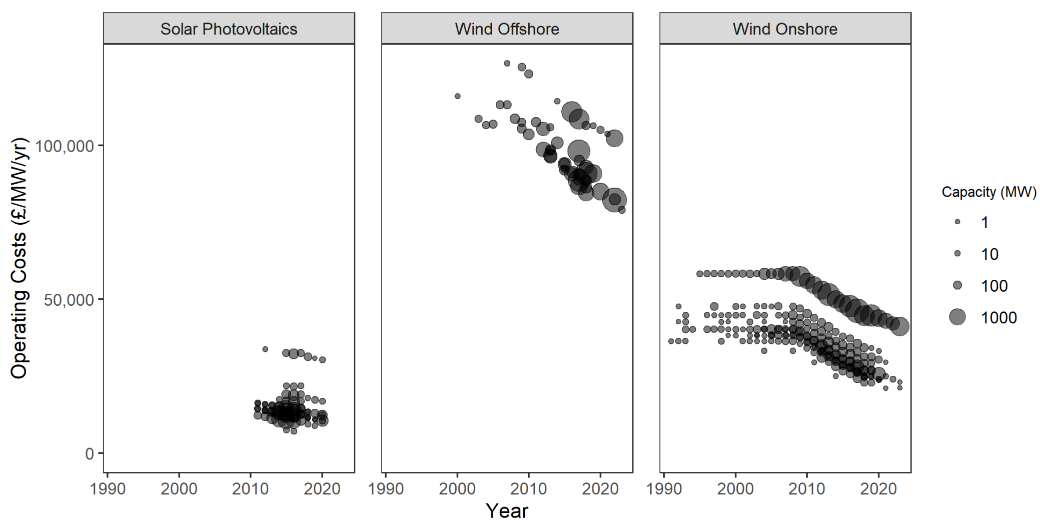
[6]For example, the locational portion of National Grid's transmission charge can vary from more than £20,000/MW/year in Scotland to less than -£10,000/MW/year near London.

[7]These add an average of roughly £45,000/MW/year to the costs for offshore wind projects.

Figure 4.3: Estimated Project Capital and Operating Costs by Year



(a) Capital costs



(b) Operating costs

Notes: This figures shows the estimated costs over time. Each point represents the total amount of proposed capacity of a given technology type at a given cost level. Capital costs are at the top and operating costs are at the bottom.

Learning-by-doing

Finally, a potentially critical wider benefit of the wind and solar projects under consideration here is learning-by-doing (item 7). The early adoption of these technologies can create learning spillovers that drive down costs, providing an external benefit to future projects and lowering the costs of climate change mitigation (Borenstein, 2012). The rapid decline in the costs of wind and solar power over the past few decades suggests these learning effects could be substantial. However, actually quantifying the value of this kind of learning is very challenging. Here I rely on a paper by Newbery (2018) which sets out a methodology for calculating the maximum justifiable learning-by-doing subsidy for onshore wind and solar power. Unfortunately it is not straightforward to adapt this method for offshore wind. Recent cost declines could point to significant learning occurring, so here I assume that the learning benefits for offshore wind are twice the level for onshore wind. Given the important role the UK has played in supporting this nascent technology the learning effects could be particularly important. I return to this issue when considering aspects of the results that involve comparing onshore and offshore wind.

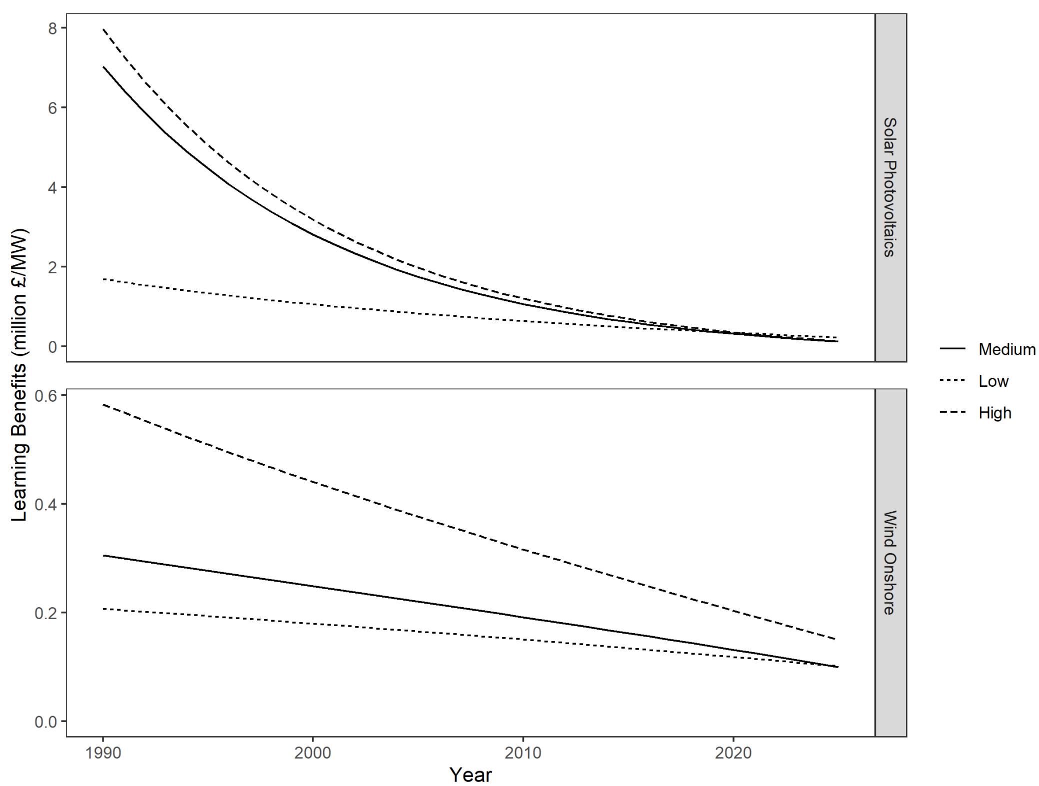
To measure the learning-by-doing benefits created by constructing a wind or solar project I rely on a paper by Newbery (2018). The paper sets out a methodology for calculating the maximum justifiable learning-by-doing subsidy for wind and solar power. Based on this I estimate learning benefits in 2015 of £600,000/MW for solar and £250,000/MW for onshore wind. These values decline steadily over time as each technology matures, and so can be substantially higher for some of the earliest projects. Unfortunately it is not straightforward to adapt this method for offshore wind. Recent cost declines could point to significant learning occurring, so here I assume that the learning benefits for offshore wind are twice the level for onshore wind.

To try and capture some of the uncertainty in this particular impact I also create "low", "medium" and "high" sensitivities. To do this I use the range of scenario assumptions set out in the paper in Table 1. In particular, the "low", "medium" and "high" sensitivities for solar projects were taken from columns F, C and B respectively, and for wind projects from K, J, and I respectively. The optimal subsidy is scaled based on the average global installed capital cost for wind and solar projects in 2015, based on data from IRENA. The resulting values can be seen in Figure 4.4.

4.2.4 Determinants of planning approvals

To evaluate the planning process I employ a relatively straightforward regression model that aims to identify which categories of costs and benefits drive project approvals. The observations here are the roughly 3500 wind and solar projects in my sample. The dependent variable is a binary indicator for

Figure 4.4: Learning-by-doing Benefits from a New Wind or Solar Project by Year



Notes: This figure shows the changing learning-by-doing gains from installing a new wind or solar project in a given year over the sample period. "Low", "medium" and "high" sensitivities are shown by the different dashed lines.

whether or not a project was approved. The independent variables of interest are the various key costs and benefits associated with each project. All these costs and benefits were calculated as described above and discounted to consistent present value terms. The resulting regression is as follows:

$$approve_{ict} = \beta_1 local_i + \beta_2 nonlocal_i + \theta_t + \lambda_c + \epsilon_{ict} \tag{4.1}$$

The dependent variable is a binary approval decision indicator, *approve*, for each project, i, in county, c, in year, t and it is regressed on both the local net benefits, *local*, and the non-local net benefits, *nonlocal*. The resulting coefficients capture the impact of a positive change in their respective value categories. I also scale each coefficient such that it reflects the percentage change in approval probability for a £10 million improvement in net benefits. This improvement could be realized through higher benefits (e.g. earning a higher electricity price or displacing a larger amount of emissions) or through lower costs (e.g. cutting the costs of constructing the project or reducing the impacts on nearby property values).

To control for unobservable determinants of planning approvals I also include a set of time, θ, and location, λ, fixed effects. The time fixed effects are year-of-sample and capture general national trends in the likelihood of projects being approved. The location fixed effects are for each local authority and capture general differences in planning processes across jurisdictions. Because local authorities are the administrative units responsible for reviewing planning applications this means the results are identified using within-authority variation from the range of projects that each local authority receives. I estimate these regressions first by pooling across all projects and then separately for wind and solar projects.

This model allows me to test a number of interesting hypotheses. First, for an idealized global social planner we might expect to find that all improvements in new benefits have the same impact on approval likelihood, irrespective of where they occur (i.e. $\beta_{local} = \beta_{nonlocal} > 0$). A national planner is likely to get pretty close to this, although most of the carbon emission reduction benefits likely accrue to other countries. However, a local planner might deviate significantly from this. In fact we might reasonably expect them to primarily pay attention to the local net benefits as these are the ones that directly affect actors in their jurisdiction (i.e. $\beta_{local} > \beta_{nonlocal}$=0).[8]

To further explore some of the dynamics at work, I extend the analysis to see if there are differential effects based on local political preferences. Survey data consistently shows that strong majorities in the UK express concern about climate change and support for renewable energy, including when asked

[8]Altruistic motivations that extend beyond narrow self-interest are an obvious exception to this though.

whether they would be happy to have a large scale renewable energy development in their area (BEIS, 2020*b*). Despite this broad support, it is still the case that concern about climate change and support for renewable energy has tended to be weaker amongst conservative voters (NatCen, 2018). As such political voting behavior could plausibly act as a proxy for variation in local attitudes towards nearby wind and solar projects. To explore this I collect data on local elections from Election Centre. In the UK, councillors for each local authority are elected at least every four years and the vast majority of councillors are affiliated with one of the main UK political parties. Using this data I construct an indicator for whether a local authority is politically conservative based on whether it has a majority of Conservative party councillors. I then interact this with the local and non-local variables to see if the planning process differs in conservative areas relative to more liberal areas.

A second possible source of differential effects that I examine is the impact of a project being decided by the national planning agency rather than at the local level. To do this I now interact the variables of interest with an indicator for whether the planning authority in charge was national or local. It was noted earlier that the decision to review a project at the national level is based on whether the project is larger than 50MW. As such the projects considered by national planners are systematically larger.[9] This is mitigated slightly by the fact that I also included the appealed projects in the national planner category. This is because the final decision for these projects was in fact made by the national Planning Inspectorate. Given that the vast majority of projects are below the 50MW threshold, the inclusion of appealed projects has the added benefit of making the split between the numbers of local and national projects more balanced.

4.2.5 Quantifying the extent of misallocated investment

The final analysis I conduct is to quantify the extent of insufficient or misallocated investment. A key issue the regression analysis examines is the prospect that not all costs and benefits may be weighed equally during the planning approval process. For example, if particular emphasis were to be placed on avoiding adverse impacts on local property values, the result may be that socially beneficial projects are consistently refused, slowing the deployment of renewable energy. Even if the aggregate deployment of renewable energy is unaffected the planning process could still create a systematic bias towards approving more expensive projects, again on the basis that they have smaller

[9] I did consider using a Regression Discountinuity design for this part of the analysis. However, the data is simply not rich enough to have enough observations around the threshold. This approach is also undercut by the fact the 50MW threshold is public information and so it can be gamed if developers think having a national planning decisionmaker is desirable.

impacts on local property values. This could take the form of building solar power instead of wind, even though the UK has far better wind resources than it does solar potential. Alternatively this misallocation could take the form of building more remote wind projects, or moving projects offshore, even if they are ultimately more socially expensive due to higher construction costs or requirements to transmit power over longer distances.

To try and quantify the potential for insufficient or misallocated investment I identify the set of projects that would have produced the observed annual deployment of renewable energy at least cost to society. To do this I group projects by their actual or expected start year and then rank them in order of their social net present value. I sum up the least cost set of projects necessary to reproduce the actual observed capacity additions for each year. I then compare the difference in cumulative total social net present value between this least cost set of projects and the actual set of projects that were built. This also allows me to examine which projects account for the difference, and whether they were approved or denied planning permission.

In thinking about the role of NIMBYism and local interests in the planning process, it is worth being clear about what is actually meant by NIMBYism. NIMBYism can be more precisely defined as "the combined preference for the public good and a refusal to contribute to this public good" (Wolsink, 2000). The public good of interest here is the provision of renewable energy, with the aim of mitigating climate change, reducing local pollution, and ensuring secure energy supplies. The refusal to contribute arises when there is local opposition to having a project sited nearby. Much of the literature on community acceptance of renewable energy has challenged the NIMBY characterization as oversimplistic (Wolsink, 2000; Bell et al., 2013; Burningham, Barnett and Walker, 2015; Rand and Hoen, 2017; Hoen et al., 2019). For instance, whilst NIMBYism is usually characterized by a narrow emphasis on individual self-interest, actual stated opposition is frequently expressed in terms of concerns about the impact on the community, or the fairness of the political process. Moreover, even classic narrowly self-interested NIMBYism need not be widespread in a given locality for it to have an effect if the NIMBYs are a particularly vocal minority that can exert outsize influence. Conflicts over proposed projects can also be exacerbated by pre-conceived notions of local residents as parochial obstacles and project developers as extractive corporate outsiders.

In this study, I primarily think about local interests and NIMBYism in terms of the community-level decisions made during the planning process. Part of the motivation is that a decision to refuse a project in this way is probably the most straightforward and impactful way that a "refusal to contribute to [the] public good" could be expressed. These community-level decisions are still determined by the complex interaction of individual attitudes, political power and the idiosyncracies of local circumstances that prior studies have highlighted. Rather than examining these underlying drivers of each planning decision, my main focus is on whether local communities in general make decisions that systematically reflect their own economic self-interest, and whether this imposes economic costs on wider society through the underprovision of public goods that are otherwise broadly supported.

4.3 Results

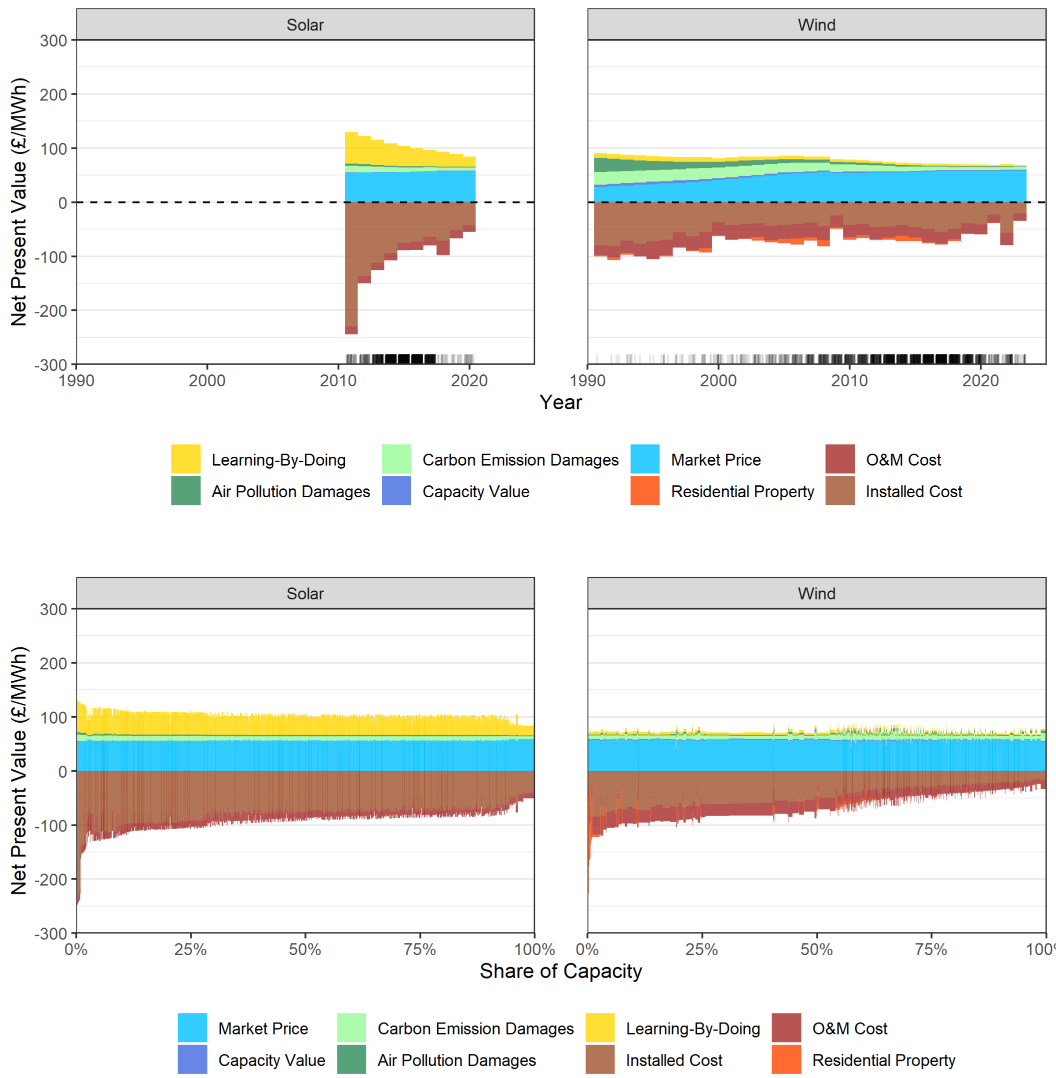
Figure 4.5 summarizes the estimated costs and benefits for all the wind and solar projects studied here. The top panel shows how annual averages of these costs and benefits have changed over time. The large declines in project capital costs are clearly visible and reflect the substantial technological progress that has taken place over this period. The declining environmental benefits over time are also striking and reflect the fact that the marginal electricity production being displaced by a project built in 1990 was much dirtier than for a project built in 2020. The bottom panel shows the full ranking of projects in order of their total net present value. This makes clear the significant heterogeneity across projects, particularly with regard to the local property value impacts. Plots including the subsidies can be found in the appendix.

Table 4.3 presents the results of the planning process analysis. When only controlling for year fixed effects (columns 1-3) I do not find any significant evidence of sensitivity to local impacts. However, when I add county fixed effects to look at within-county variation (columns 4-6) the local impacts that have a large, positive and statistically significant effect on the likelihood of receiving planning approval. Here I find that if a wind project imposes £10 million in losses to nearby residential property values, it will be 3% less likely to be approved. The results is that local authorities are responsive to local factors for the range of projects in their jurisdictions.

The same magnitude of responsiveness is not apparent for non-local impacts. For instance, a similar £10 million increase in capital costs or a £10 million decrease in electricity revenues has a negligible effect on the chance of approval. This fits with the hypothesis set out earlier that local decisionmakers are incentivized to focus on impacts on local actors whilst ignoring other impacts that are largely externalized to non-local actors. Interestingly, the coefficient on non-local impacts is actually negative and statistically significant, although the coefficient is an order of magnitude smaller than the coefficient for local impacts. This small size of the coefficient highlights the relative lack of attention paid to these non-local factors.

Table 4.3 also examines whether these effects are heterogeneous by political leaning or the extent of local control of the decision. When looking at the signs of the interaction terms the results are as expected. More conservative areas are more sensitive to local impacts, consistent with a pattern of con-

Figure 4.5: Estimated Project Costs and Benefits



Notes: This figures shows the estimated project-level costs and benefits for all the projects submitted for planning approval since 1990. All value categories are consistent with those described earlier and have been converted to consistent levelized net present value terms in £/MWh. These values use a 3.5% real discount rate in line with UK Treasury guidance. Assuming a higher 7% real discount rate produces estimates more in line with industry figures on private developer levelized costs. The top panel shows how average costs and benefits over time. In each year the median was calculated for each value category across all projects that were or would have been commissioned in that year. The black dashes at the bottom of the plot indicate the number of projects in a given year to convey when the bulk of projects were being proposed and commissioned. The bottom panel shows the full ranking of projects in order of their total net present value. The width of each bar is determined by the capacity of each project.

servative opposition toward wind farms. Similarly, national planning officials are less sensitive to local impacts and more responsive to non-local impacts. In both cases though it should be noted that the observed differences are not statistically significant.

Table 4.3: Planning Process Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.137	−0.550	0.277	2.956*	2.354	3.049*
	(0.634)	(0.694)	(0.816)	(1.300)	(1.563)	(1.502)
Local (Conservative)		2.854			1.739	
		(1.735)			(2.770)	
Local (National Planner)			−0.542			−0.612
			(1.287)			(2.295)
Non-Local	−0.285***	−0.218*	−1.058	−0.282**	−0.260*	−0.962
	(0.084)	(0.095)	(0.836)	(0.091)	(0.101)	(0.879)
Non-Local (Conservative)		−0.365†			−0.110	
		(0.208)			(0.229)	
Non-Local (National Planner)			0.792			0.686
			(0.841)			(0.881)
R-Squared	0.060	0.066	0.068	0.236	0.235	0.243
N	1810	1804	1810	1810	1804	1810
Wind	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Solar	-	-	-	-	-	-
Year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	-	-	-	*Y*	*Y*	*Y*

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Notes: This table shows the impact on approval probability from changes to local vs non-local project impacts. Each coefficient has been scaled to reflect the % change in approval probability for a £10 million improvement in its respective value category. Wind and solar projects are considered separately.

Given the lack of local impacts from solar projects, the extent of misallocated investment is relatively minimal, amounting to roughly £0.5 billion by 2018. This is small in both absolute and relative terms, amounting to 4% of the aggregate lifetime capital and operating costs for all the solar projects built over this period.

Wind power, on the other hand, is a different story. The significant heterogeneity in costs and benefits across wind projects, and the apparent tendency for local factors to be weighted much more heavily than non-local ones, creates real scope for insufficient or misallocated investment. The top row of Figure 4.6 shows that the potential gains from more efficiently reallocating investment across all the proposed wind projects amounted to £27 billion by the end of 2018. Moreover, around £20 billion of these gains come from switching to projects that were refused planning permission, indicating that the main source of this misallocated investment is the planning process itself. To give some sense of scale, this £20 billion in foregone gains is equivalent to 25% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

To understand which inefficiencies in the planning process might be driving this misallocation, I segment the foregone gains into those arising from swapping an existing project for one that has a) larger local impacts, or b) smaller local impacts.

I find that switching to projects with larger local costs is responsible for £4 billion of the £20 billion in potential gains. This suggests that the kind of NIMBYism concerns raised by the earlier regression analysis do appear to manifest in real economic costs. These costs arise because of an apparent bias toward approving projects that are more remote or located offshore, even when these are more costly for society as a whole.

Interestingly, I also find that switching to projects with smaller local costs is responsible for £6 billion of the £20 billion in potential gains. Given the earlier finding that planning decisionmakers are particularly sensitive to local impacts, it seems odd that high local cost projects would ever be approved over some alternative project with lower local costs. However, a number of important tendencies in the planning process might contribute to planning officials allowing projects that impose substantial local costs to go ahead. For example, the planning process emphasizes the need for all localities to do their part in combating climate change through supporting renewable energy. This creates a pressure for all local authorities to approve at least some wind or solar capacity in their jurisdiction, even if there are less locally costly projects located elsewhere. Table 4.3 provided supportive evidence for this because any responsiveness to local impacts was only found using the within-county variation. Additionally, the planning process also allows for particular consideration of the harms from cumulative impacts as multiple projects are added or extended in a given area. This creates a bias toward building a small number of projects in each jurisdiction, reducing the scope for renewable energy capacity to be concentrated in a select few areas.

The desire to share the burden of renewable deployment widely and avoid large concentrated deployment seems understandable on its face. However, this runs contrary to the non-linear nature of local impacts identified in this study. The intuition that the first wind turbine in a given area has a much larger incremental impact than adding a tenth or a hundreth is supported by the capitalization analysis. This means there could be substantial gains from concentrating capacity at larger projects in fewer areas. This is especially true in the context of renewable energy where the good being produced is perfectly homogenous and is provided over a national network that largely removes the need for siting supply locally. A key challenge to achieving this is overcoming distributional concerns and coordinating across jurisdictions. I return to discuss this issue in the conclusion section.

An important caveat with the analysis set out here is that much of these apparent gains could plausibly reflect shortcomings in the capitalization treatment effects being used. Despite going further than any previous study to estimate the local and non-local impacts of these projects, my approach may simply lack sufficient detail to fully account for the the idiosyncracies of each local area and the projects being proposed. This is particularly the case for the small number of very high local cost projects mentioned above. For any given project, planning officials will have a better understanding of their specific circumstances, and so some humility about the ability of this kind of analysis to second guess those decisions is probably in order.

To illustrate this I repeat the analysis, but this time I drop the small number of projects with the largest local costs from being considered as possible swap candidates.[10] This should prevent the analysis from being overly driven by a small subset of outlier projects with very large local impacts.[11]

As expected, the bottom row of Figure 4.6 makes clear that constraining the portfolio of possible projects reduces the potential scope for misallocated investment. The total foregone gains falls slightly to £24 billion, of which £17 billion comes from switching to projects that were refused planning permission. Notably though, a much larger portion of these foregone gains (£12 billion) is now achieved by switching to more locally costly projects. At the same time the gains from switching away from high local cost projects is also drastically reduced (£2 billion), consistent with the most locally costly projects being excluded from the analysis. This strengthens the case for NIMBYism playing an important role in driving planning outcomes that systematically refuse societally beneficial projects.

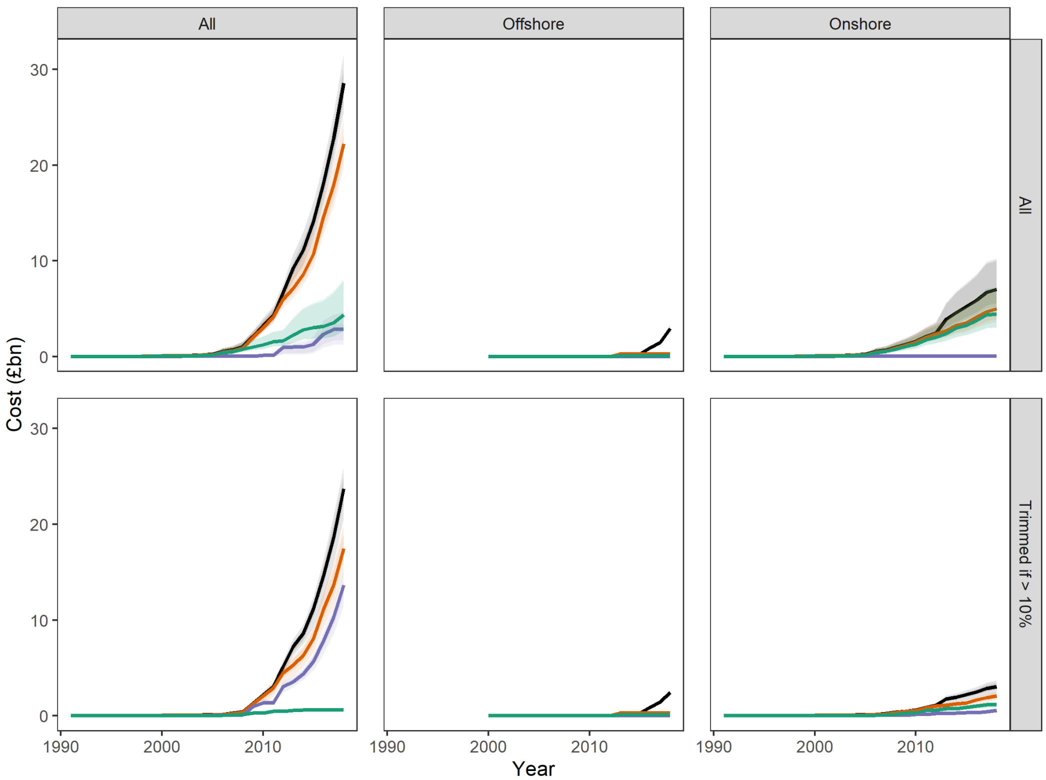
A major contributor to the misallocation described here is an apparent overinvestment in offshore wind, with the hypothetical least cost scenario consistently reallocating towards cheaper onshore wind projects, even where these onshore wind projects incur greater local costs. However, there is significant uncertainty in one of the key determinants of this tradeoff between onshore and offshore wind: the learning-by-doing benefits experienced by these two technologies. Whilst I have already assumed that offshore wind has learning benefits that are twice those of onshore wind, it is certainly plausible that the difference is even greater.

To explore the impact of this issue I repeat the same least cost scenario analysis, but this time I do so separately for onshore and offshore wind. The total potential gains from reallocation now fall significantly to £10 billion. As before the planning process continues to be a major factor, with £7 billion of these foregone gains from projects that were refused planning permission. This is equivalent to almost 9% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

[10] Here I drop all projects with local costs that are more than 10% of a project's total capital and operating costs. This amounts to excluding roughly 5-15% of wind capacity.

[11] This tends to be driven by the combination of placing a small amount of capacity near a large urban area, such as in an industrial park near a town or city.

Figure 4.6: Misallocated Investment Analysis for Wind Projects



Notes: The potential gains from reallocating wind and solar investment are shown over the 1990-2018 period. Colors indicate different subsets of the potential gains: total gain (black); gains based on refused projects (orange); gains based on refused projects that lead to lower local costs (green); and, gains based on refused projects that lead to higher local costs (purple). The central line represents the median scenario from the estimated sensitivities. The shaded area represents the range between the tenth and ninetieth percentiles from the estimated sensitivites.

The vast majority of the misallocated investment is driven by switches made amongst onshore wind projects. Overwhelmingly this comes from switching away from a small number of high local cost projects, with misallocation from possible NIMBYism falling to around £0.5 billion. This leads to an interesting conclusion: if the UK's investments in offshore wind have indeed resulted in substantial learning-by-doing, one factor that can claim a large share of the credit is the NIMBY objections to onshore wind. However, if offshore wind learning-by-doing has been relatively muted, NIMBYism toward onshore wind will have cost the UK dearly, increasing the cost of its deployment of wind power by anywhere from 5-15%.

4.4 Conclusions

In this paper I estimate the economic costs from misallocated investment arising from the planning process for renewable energy projects. Based on my analysis of the planning process I find that planning officials place particular weight on local factors when making their decisions. This is consistent with the fact that the vast majority of the planning decisions for wind and solar projects are made at the local level. I estimate that this has resulted in societally beneficial projects being systematically refused, substantially increasing the cost of the UK's deployment of wind power. A significant portion of this misallocation arises due to tendency to avoid projects that create signficant local impacts, suggesting NIMBYism is a real concern. Interestingly another large share of these misallocation costs also arise from a few smaller projects with relatively large local impacts, pointing to a wider set of issues with the planning process. Solar projects, on the other hand, do not appear to have significant adverse local impacts. This has meant solar projects are approved at much higher rates and are subject to negligible risks of misallocated investment.

There are a range of policy solutions that could remedy this misalignment between local and wider societal incentives. The most straightforward solution involves making direct transfer payments to affected local residents and businesses. Probably the clearest example of these kind of payments are community benefits funds. These provide payments from the project owner to the local community, usually in the form of grants, awards, stipends for community organizations or even discounts on electricity bills. The decision to provide these community benefits is currently voluntary so they can vary significantly in prevalence, size and structure. Public registers where developers provide information on their community engagement suggest that funds for onshore wind projects have often amounted to around £2,000-3,000/MW/yr. The latest government guidance calls for developers to adopt funds with a value of £5,000/MW/yr. Whether this guidance is being followed is hard to gauge, but the most recent register information for Scotland indicates that for many projects it is.

My analysis suggests the local impacts of wind projects on local property values have a median of around £3,500/MW/yr, which may suggest that the current scale of support being negotiated is appropriate. However, this masks significant heterogeneity in local impacts: the top 25% of projects have local impacts greater than £21,000/MW/yr and the top 10% have local impacts greater than £75,000/MW/yr. As such there may be an argument for significantly increasing the value of community payments in certain instances to more adequately compensate local residents. This should help prevent societally beneficial projects being refused planning permission purely on the grounds that they create local impacts that are not being adequately offset by an equivalent level of local compensation.

The heterogeneity in local impacts also points to another way in which transfer payments could be beneficial that has yet to be tested. My analysis indicates that several projects with large local costs have gone ahead. It is possible that this could be because planning officials and local residents sometimes misperceive the true local impacts, or there is a lack of political power amongst the affected communities to resist development. However, my analysis suggests that this may also be due to a coordination problem across jurisdictions. If building wind and solar capacity does indeed impose a declining incremental cost on local communities, there is a compelling argument for avoiding the tendency to "share the burden" by installing at least some capacity in most jurisdictions. Instead there could be large gains from concentrating more capacity at larger projects in a smaller number of designated areas.

This has clear distributional consequences for the communities that are exposed to this kind of concentrated deployment of renewable energy. However, making transfer payments between jurisdictions could provide the necessary compensation to facilitate a more societally beneficial reallocation of investment. In this case communities that do not want to be exposed to new renewable energy deployment would make payments that compensate other communities that are willing to host a more concentrated deployment of renewable energy nearby. Ensuring both communities get appropriate credit for investing in renewable deployment could go a long way to ensuring all jurisdictions share the financial burden, even if they are not all physically hosting capacity.

An alternative to providing compensation payments is outright local ownership. This has certainly been growing and there is some evidence in the UK that the direct local benefits provided by these projects are in fact much larger than for privately owned projects. A key challenge here is scalability. There is currently roughly 250MW of community owned capacity in the UK (Braunholtz-Speight et al., 2018). This represents about 1% of total renewable electricity generation. Whilst it might be possible for this to be increased, it seems unlikely that local communities can deploy the kind of financial and technical resources that larger private companies can in order to roll out renewable energy at the scale and pace that is required.

A final option raised by the findings in this paper could be to give national planning officials a larger role in the approval process. My analysis suggests that national decisionmakers have a more balanced approach to weighing the local and non-local costs and benefits of these projects. This may be because national planning officials are less beholden to local political considerations, or perhaps they are just more likely to have the necessary institutional capacity to effectively consider projects at this scale. In either case more national oversight and support might be beneficial, especially if it can facilitate better coordination across local jurisdictions. This could be achieved by setting stricter national planning guidelines, lowering the threshold for projects to be moved from local to national jurisdiction, or by streamlining the appeal process. One potential downside of this solution is that shifting too much control out of local hands could backfire if it results in local residents believing their concerns are not being heeded.

Ultimately finding the best policy solution will require further research and experimentation. The findings in this paper on the costs imposed by the existing planning process suggest this work is sorely needed.

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